Location factors and agglomeration economies in the hotel industry: the case of Spain

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Received 8 October 2021
Revised 9 March 2022
6 July 2022
Accepted 1 August 2022

Abstract

Purpose – This research investigates the effect of accessibility to points of tourist interest (buffer) and direct and indirect spatial spillover effects of agglomeration economies on tourism industry revenues in Spain.
Design/methodology/approach – Data were collected from the Bureau van Dijk's (BvD) Orbis global database. The data were analysed using a spatial econometric model and the Cobb–Douglas production function.
Findings – This study reveals that hotels located inside the buffer zone of points of tourist interest achieve better economic outcomes than hotels located outside the buffer. Furthermore, the results show that there is a direct and indirect spatial spillover effect in the hotel industry.
Practical implications – The results provide valuable information for identifying areas where the agglomeration of hotels will produce a spillover effect on hotel revenue and the area of influence of location characteristics. This information is relevant for hotels already established in a destination or when seeking a location for a new hotel.
Social implications – The results of this study can help city planners in influencing the distribution of hotels to fit desired patterns and improve an area's spatial beauty.
Originality/value – The paper provides insights into how investment, structural characteristics, reputation and location affect hotel revenue.

Keywords Hotel industry, Spillover effects, Hotel revenue, Spatial policy diffusion, Clustering, Spatial accessibility

Paper type Research paper

1. Introduction

The hotel industry is one of the most important industries fuelling global socioeconomic development, especially in countries like Spain. However, traditional hotels currently face challenges to preserve and improve industry efficiency (Zhang *et al.*, 2020). Since 2020, the COVID-19 crisis has affected the accommodation industry (Nicola *et al.*, 2020). Moreover, the rise of nonstandard accommodation (e.g. Airbnb) has hit the industry (Zhang *et al.*, 2020). To identify hotels with a greater capacity to withstand periods of crisis in the tourism industry, we investigate a relevant competitive advantage of hotels: location (Cheng, 2013).

Funding: This research was funded by Junta de Andalucía and FEDER funds (No: B-SEJ-381-UGR18) and the Spanish State Research Agency (No: PID2019-110941RB-I00).

European Journal of Management and Business Economics
Vol. 34 No. 1, 2025
pp. 1-22
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-10-2021-0273

The literature classifies variables related to hotel location factors into three groups: (1) hotel accessibility, which includes the main points of access such as bus/train stations and airports (Kim *et al.*, 2020; Lado-Sestayo *et al.*, 2020); (2) proximity to tourist attractions, including heritage sites and the coastline (Valentin and O'Neill, 2019); and (3) spillover effects caused by economic agglomeration and policy diffusion observed in the hotel industry (Zhou *et al.*, 2019). However, few studies have analysed the relationship between these location factors and spatial spillover effects (Lado-Sestayo *et al.*, 2020) and even less so the area of influence (buffer) of points of tourist interest or the relation between spatial spillover effects and mechanisms of policy diffusion in the hotel industry.

Policy diffusion refers to the fact that the policies of one entity are influenced by the policies of other entities. The bulk of the literature on policy diffusion examines policy spread by state and local policymakers (Gilardi and Wasserfallen, 2019). The diffusion literature considers four mechanisms of diffusion: coercion, competition, imitation and learning (Shipan and Volden, 2008). Three mechanisms may lead to the presence of spatial spillover effect, namely competition, imitation and learning (Chica-Olmo *et al.*, 2021). Spatial spillover refers to the fact that one company's activities usually impact on other nearby companies (Tallman *et al.*, 2004). In this line, Barros (2005) indicated that hotels can obtain positive spillover effects from neighbouring hotels. This effect is accounted for in the models through the presence of spatial autocorrelation.

The aim of this study is to explain the effect of accessibility to certain points of tourist interest (heritage sites, airports and the coast) and the spatial spillover effect of the hospitality industry on revenue. Also, to eliminate specification problems, we included other relevant predictor variables as controls, which are divided into three groups: structure (size and number of stars), investment (workforce and capital investment) and reputation (customer ratings). Lastly, spatial econometric models were used. The findings of this study provide useful information for selecting the best location for new hotels in a given destination and detecting the effect of policy diffusion on hotel revenue.

2. Literature review

Agglomeration economies are defined as positive (or negative) externalities resulting from the geographic clustering of firms (Myles Shaver and Flyer, 2000). These economies are linked to the geographical proximity between companies in regions with location advantages, thus giving rise to competitive advantages (Porter, 1998). Three main positive externalities are related to firm location: (1) knowledge spillovers; (2) pool of specialised labour; and (3) specialised input provided (Myles Shaver and Flyer, 2000). The literature on agglomeration economies suggests that geographic clusters improve firm performance due to better production and/or demand, which in turn causes industries, such as technology, hospitality, food and retail, to choose to cluster (Canina *et al.*, 2005).

Agglomeration of tourism businesses can improve their revenues via location-specific externalities (Tallman *et al.*, 2004). In tourism, agglomeration economies are significant due to the marked localisation of services, which are considered inseparable in time and space (Kim *et al.*, 2021). Tourism markets are spatially concentrated in a specific place, known as spatial clusters. Hotels located in spatial clusters have advantages in terms of both supply (access to suppliers and services) and demand (lower costs for consumers) (Canina *et al.*, 2005). In turn, agglomeration economies are linked to policy diffusion, leading hotels to form spatial clusters (Ferreira Neto, 2021).

Different spatial interactions such as the domino effect or the entry and exit of competitors cause spatial spillover effects that motivate companies to cluster geographically, thus leading to higher revenues (Tallman *et al.*, 2004). Hotel revenues depend on agglomeration economies due to the benefits that companies obtain from being close to others (Cruz and Teixeira, 2010).

This study uses four types of explanatory variables to determine the factors that impact hotel revenue: investment, structural characteristics, reputation and location. The literature has linked these factors to room rates, but few authors have analysed how they affect hotel revenue (Öğüt and Onur-Taş, 2012).

Investment: The Cobb–Douglas production function is probably the most widely used function to explain industrial production and has been employed in the hotel industry (Barros, 2004) and agglomeration economies (Viladecans-Marsal, 2004) where the main factors of production are workforce and capital investment.

Structural characteristics: One of the structural features considered in some studies is hotel size measured by number of rooms, which is directly related to hotel revenue (i.e. revenue per available room) (Kim *et al.*, 2013; Öğüt and Onur-Taş, 2012). Another structural feature that could be related to revenue is star rating. Star rating includes aspects such as physical characteristics like room size and facilities (Pawlicz and Napierala, 2017). The number of stars depends on factors like room size, air conditioning and other amenities. In general, hotels with higher star ratings generate more revenue (Martin-Fuentes, 2016).

Reputation: Another factor that has received considerable attention as an explanatory variable for hotel revenue is customer ratings. Studies have linked customer ratings to hotel prices and revenue (Blal and Sturman, 2014). Öğüt and Onur-Taş (2012) examined how an increase in customer ratings increases hotel industry revenue in some European destinations, such as Paris and London. Elias-Almeida *et al.* (2016) found that only customer delight generates more favourable results for hotels by increasing sales, customer loyalty, word-of-mouth communication and repurchase intentions.

In short, a large body of literature has linked hotel industry revenue with variables relating to these three types of factors. However, location factors have been little studied.

2.1 Spatial analysis of hotel location

Spatial analysis is used to identify the location patterns of hotels in different localities and their causes (Luo and Yang, 2016). The findings of spatial analyses are useful for predicting hotel industry behaviour and determining the importance of other factors such as resources and culture (Roehl and Van-Doren, 1990). The academic literature has sought diverse ways to explain these patterns at the national, regional and inter- and intra-regional scales (Yang *et al.*, 2014). In this regard, various techniques have been used, amongst them choropleth maps (Roehl and Van-Doren, 1990), spatial statistics (Luo and Yang, 2013), the monocentric model (Yang *et al.*, 2012) and agglomeration models (Kalnins and Chung, 2004).

Spatial patterns amongst hotels can be understood through the perceived agglomeration effects of their geographical concentration. The agglomeration model explains these patterns according to the relative location of entry hotels with respect to incumbent hotels (Yang *et al.*, 2014). Several studies have shown that entry hotels tend to be close to other competitors (Baum and Haveman, 1997) and a higher density of hotels increases the probability that entry hotels will choose that location (Kalnins and Chung, 2004).

Additionally, agglomeration models consider differences between entry hotels and incumbent hotels in terms of hotel ratings (Kalnins and Chung, 2004), hotel size (Yang *et al.*, 2012) or hotel brand (Kalnis and Chung, 2004).

For the empirical estimation of spatial agglomeration, spatial models have been developed, e.g. the spatial autoregressive (SAR) model and the spatial error model (SEM). The SAR model focusses on the interaction between dependent variables, while the SEM estimates the effect of spatial interaction between perturbances (Wang *et al.*, 2019). SAR models have been used in the hotel industry to determine the effects of agglomeration on hotel and restaurant demand (Skrede and Tveteraas, 2019), hotel location choices (Kalnins and Chung, 2004), hotel prices (Balaguer and Pernías, 2013) and labour productivity (Kim, 2020).

However, these models have not been used in the literature to examine the effects of agglomeration on hotel performance in terms of profitability (e.g. Marco-Lajara *et al.*, 2014) and the evidence is mixed (Lado-Sestayo *et al.*, 2017). There is positive empirical evidence for the effect of agglomeration on hotel revenues (Chung and Kalnins, 2001). It has been shown that close competitors have access to resources (e.g. knowledge transfer, technology) that other competitors which are not close in space lack (Tallman *et al.*, 2004).

In addition, to take advantage of the externalities of stronger firms and improve revenues, weaker firms tend to locate close to stronger ones (Myles Shaver and Flyer, 2000). There is evidence in the literature of a negative relationship between agglomeration and profitability (Marco-Lajara *et al.*, 2014) due to the competition caused by proximity and diminishing marginal returns (Baum and Haveman, 1997). In the hotel industry, revenues are the most accessible variable given that data are published annually together with company accounts. In addition, this variable is related to the production function (Assaf, 2012).

2.2 Production function

Empirical studies on the tourism and hospitality industry have used the Cobb–Douglas function to measure the impact of operational strategies and policies on industry performance, particularly in terms of perceived costs and revenues (Arbelo *et al.*, 2018).

Studies using revenue as the dependent variable (Assaf and Magnini, 2012) have been conducted for tourism industries in European countries such as Portugal (Barros, 2004) and Spain (Pérez-Rodríguez and Acosta-González, 2007), as well as in non-European destinations such as Taiwan (Chen, 2007), the United States (Assaf and Magnini, 2012) and the Asia–Pacific region (Assaf, 2012). Similarly, in the literature on the economic effects of agglomeration, attempts have been made to explain other variables such as labour productivity (Anderson *et al.*, 1999). In this other field, the strategies used to estimate agglomeration effects are based mainly on the Cobb–Douglas functional form (Fernandes *et al.*, 2017).

An alternative functional form used in agglomeration studies is the translog function. Translog is considered an optimal function in some studies (e.g. Arbelo *et al.*, 2018; Martín-Rivero *et al.*, 2021) because it does not require strict assumptions such as "perfect" or "smooth" substitution between production factors or perfect competition on the production factors market (Pavelescu, 2011). However, the translog function is more difficult to manipulate mathematically (Martins *et al.*, 2012) and can lead to problems of collinearity (Fernandes *et al.*, 2017; Lionetti, 2009) or higher correlation (Vives and Jacob, 2020) due to the large number of parameters that must be estimated in each production factor (Pavelescu, 2011).

For this reason, other studies have argued that the Cobb–Douglas function is the most appropriate function (Assaf and Magnini, 2012; Deng *et al.*, 2019) as it satisfies properties such as explicit representability, parsimony, flexibility and uniformity (Bhanumurthy, 2002); it is easier to use for estimating and interpreting elasticities (Deng *et al.*, 2019), and largely approximates a production process (Reynes, 2017). Given these qualities, the Cobb–Douglas production function is used for the quantitative analysis performed in this study.

In line with other studies (Chiang and Cheng, 2014; Wannakrairoj and Velu, 2021), the Cobb–Douglas production function was estimated omitting records of hotels with no activity mainly to allow for the use of log-linear estimates. Alternatives for dealing with these cases have been proposed in the literature, such as the use of a dummy variable (Battese, 1997) or relative values (Chiang and Cheng, 2014). However, estimations obtained with transformed values could be extremely sensitive to the chosen transformation (Soloaga, 1999).

2.3 Location factors and buffer

Location choice is the most crucial decision for a new hotel (Yang *et al.*, 2012) and the hotel industry relies heavily on its strategies for choosing where to locate its establishments.

An effective location is linked to higher occupancy rate, profitability and revenue per room and will influence customer/tourist attraction and success/failure against competition (Latinopoulos, 2018; Luo and Yang, 2016). Hotels will choose to locate close to other hotels with similar characteristics to benefit from the external economies of all firms in the same environment; a behaviour that is referred to as "spatial agglomeration" (Adam and Mensah, 2014). Yang *et al.* (2014) argued that hotels are not randomly distributed but form spatial clusters due to these agglomeration economies. These spatial clusters of hotels are related to location factors.

The most frequently used measure of accessibility and proximity in these models is the distance between some points of origin and destination (Thrane, 2007). Most of the studies cited above suggest a monotonically decreasing relationship between distance to the destination's tourist attractions and hotel performance. However, the behaviour of tourists when selecting accommodation may not follow this pattern, and the effect may even disappear after a certain distance, thus giving rise to a buffer zone or area of influence around the point of interest. One methodological aspect our study aims to determine is whether it is better to specify accessibility by means of a buffer zone or to directly consider the distance between the hotel and the point of interest. Similar models have been developed to estimate the price of housing (Chica-Olmo *et al.*, 2019) and hotel accommodations (Blal and Sturman, 2014).

In accordance with Tobler's (1970) first law of geography that "everything is related to everything else, but near things are more related than distant things", hotel revenues are assumed to be spatially auto-correlated since nearby hotels are more likely to have the same (1) development goals and requirements; (2) attributes (Latinopoulos, 2018); (3) accessibility to transportation systems (Valentin and O'Neill, 2019); and (4) share complementary products offered by nearby businesses (e.g. restaurants, places of interest) (Rigall-I-Torrent and Fluvià, 2011).

Some studies have highlighted the importance of accessibility to airports, road and railroad networks for hotel guests (Lado-Sestayo *et al.*, 2020; Yang *et al.*, 2018). Given that tourists want to be well linked to the place they are visiting, transportation accessibility is an important driver of hotel location and guest satisfaction (Valentin and O'Neill, 2019; Yang *et al.*, 2012).

The distance between means of transport and accommodation has a negative effect on the number of visitors and hotel industry revenue (Montant, 2020). As the primary point of entrance in cities, airports play an essential role in accessibility (Valentin and O'Neill, 2019). Hotel guests perceive airport proximity as a benefit during their stay (Kim *et al.*, 2020) and hotel demand increases when points of tourism interest become more accessible (Yang *et al.*, 2018). Transportation to tourist destinations improves the utility and satisfaction of hotel guests, thus increasing the hotel's performance and revenue (Chou *et al.*, 2008).

In Spain, 82% of international tourists arrive by air (National Institute of Statistics [INE], 2020). The country's two main points of interest for tourism are its sun, sea, sand offering and cultural heritage (Huete-Alcocer *et al.*, 2019). Given that these are the most frequent types of tourism in Spain (Cisneros-Martínez and Fernández-Morales, 2015), we propose the following hypotheses:

H1. The spatial accessibility of a hotel to the nearest airport positively influences hotel revenue.

H2. The spatial accessibility of a hotel to a destination's main attractions (coastal and cultural) positively influences hotel revenue.

2.4 Policy diffusion mechanisms and spatial spillover effects

Hotel managers make decisions to improve performance influenced by diffusion mechanisms. Shipan and Volden (2008) considered four mechanisms of diffusion: coercion, competition, imitation and learning. The last three mechanisms are directly associated with the presence of spatial spillover effects although coercion may indirectly induce imitation.

Competition is a natural mechanism of the competitive market by which companies react in order not to lose business with respect to their closest competitors in the space.

The imitation mechanism occurs when the management of a hotel imitates the decision of the management of other neighbouring hotels, without considering whether this decision is effective. However, the learning mechanism occurs when a hotel adopts the decision of other hotels because it has learnt from their experience. Thus, similar and related companies in the same cluster create learning zones that enable knowledge spillovers and encourage learning and innovation, which in turn increases company and cluster productivity (Kim *et al.*, 2021).

According to Shaw and Williams (2009), it is easier to create human capital (as a result of observation and imitation) in geographically concentrated areas due to transparency and proximity. In the tourism industry, competitiveness, newly acquired knowledge and the imitation process can promote innovation at business level, thus improving the company's competitiveness and productivity (Weidenfeld *et al.*, 2010). In a learning environment like this, human capital and knowledge spillovers accumulated in the movement of experienced labour between cluster enterprises have an important impact on productivity (Kim *et al.*, 2021) or due to factors such as technology or knowledge transfer (Arbia *et al.*, 2010).

However, the effects of these mechanisms are not easy to separate, measure or quantify (Shipan and Volden, 2008), although they will have effects on the econometric model, giving rise to the presence of spatial spillover effects.

Policy diffusion gives rise to spatial clusters (Myles Shaver and Flyer, 2000), which are produced by two types of spatial spillover effects. The first effect is substantive spatial dependence (Anselin, 1988), which involves a spillover effect on the performance of geographically close hotels. Due to a spatial mechanism of diffusion, hotel managers might be expected to make decisions aimed at increasing revenues, such that hotels with high revenues will be located next to others with high revenues and vice versa, resulting in the presence of a spatial spillover effect of the dependent variable (substantive spatial dependence).

The second effect is indirect (LeSage and Pace, 2009). This is the spatial spillover effect of explanatory variables and occurs when factors that explain the revenue of some hotels affect the revenue of their neighbours. In this case, hotel managers' decisions with respect to some explanatory variables affect the revenues of neighbouring hotels. For example, if a hotel manager decides to increase the number of employees, this will benefit other nearby hotels, as it will be relatively easy to find trained staff. Few studies have considered the effects of spatial spillover on hotel revenue (Lee and Jang, 2012) and even fewer or none have examined the relation between spatial spillover and diffusion policies.

Therefore, two additional hypotheses regarding the location of hotels are proposed:

H3. Mechanisms of diffusion lead to the presence of substantive spillover in the hotel industry.

H4. Through mechanisms of diffusion, the explanatory factors of a hotel's revenue will affect the revenue of neighbouring hotels, thus leading to indirect effects.

3. Methodology

Ordinary least squares (OLS) is probably the most widely used method to study accommodation performance (White and Mulligan, 2002). The spatial relationship between the values of a spatially distributed variable determines spatial dependence, which is measured by spatial autocorrelation (Anselin, 1988). In the presence of spatial autocorrelation, OLS ignores spatial dependence and provides biased standard errors and inefficient estimations (Anselin, 1988). This justifies the use of more sophisticated spatial methodologies such as the spatial econometric models recently used in studies on the lodging industry (Eugenio-Martin *et al.*, 2019).

Although there are several types of spatial econometric models (Anselin, 1988; Elhorst, 2014), only two are commonly used:

(1) Spatial autoregressive model (SAR):

$$y = \rho Wy + X\beta + \varepsilon \tag{1}$$

(2) Spatial error model (SEM):

$$\begin{aligned} y &= X\beta + u \\ u &= \lambda Wu + \varepsilon \end{aligned} \tag{2}$$

where y is a vector of the values of the dependent variable; X is a matrix with explanatory variables; β is a vector of the parameters; W is a row-standardised spatial weights matrix whose elements are w_{ij}; Wy is a vector representing the spatial lag of the dependent variable; ρ is the spatial autoregressive parameter and represents the endogenous or substantive spatial spillover effects; Wu is a vector representing the spatial lag perturbations with λ as its associated parameter; and ε denotes normal vector perturbations.

In our study, a SAR model has been preferred (see section 6) and the specification is:

$$\text{ln\_Revenue} = \beta_1 i + \beta_2 I + \beta_3 S + \beta_4 R + \beta_5 L + \rho W_1 \text{ln\_Revenue} + \varepsilon \tag{3}$$

where ln_Revenue is a vector with log of hotel revenue; i is a vector of ones; I, S, R and L are matrices with investment, structural, reputational and locational variables; W_1 is the spatial weights matrix whose elements are $w_{ij} = 1/d_{ij}$, where d_{ij} represents the distance between two hotels; and β_j and ρ are the associated parameters.

3.1 Study area and data description

This study is geographically based on hotels located in Spain using financial metrics revenues per hotel. With 82.6 million international tourists in 2018 (UNWTO, 2019b), Spain occupies a prominent position within the international hotel industry (Lado-Sestayo *et al.*, 2020); one of the main generators of employment in the country. Over 2.5 million people were employed in the tourism industry in 2018, 3.7% more than in the previous year (UNWTO, 2019b). In addition, 13.5% of total employment in Spain is linked to tourism-related activities (UNWTO, 2019a). Bujosa *et al.* (2015) projected that tourism will continue to grow and develop driven by the sun, sea and sand product, which is currently the largest tourism segment in the world.

However, it is not the only tourism product that attracts international arrivals, as cultural tourism has experienced rapid growth worldwide (Huete-Alcocer *et al.*, 2019). Spain was chosen for this study as it has been the second tourist destination worldwide for several years (UNWTO, 2019a). With its 8,000 km of coastline, Spain has a wide sun, sea and sand tourism offering (IGN, 2020), as well as an important cultural tourism offering due to its 48 sites registered on the World Heritage List (UNESCO, 2020).

We obtained the data from Bureau van Dijk's (BvD) Orbis global database in 2018.

This database has been used in several studies (Kalemli-Ozcan *et al.*, 2015) as it contains data on the most important companies in each country and verifies the accuracy of the information. Although a total of 14,742 hotels were in operation in Spain in 2018 (INE, 2020), the Orbis database has information for only 2,047. Moreover, due to the lack of data for the individual analysis of some of the hotels, the study sample was reduced to 1,537 establishments. As in Chiang and Cheng (2014) and Wannakrairoj and Velu (2021), the sample was restricted to the positive values of the dependent and independent variables to enable the use of log-linear estimates and better interpret the elasticities. Thus, non-operating

hotels in 2018 were eliminated from the analysis and a final sample of 1,015 hotels was obtained. The study uses a larger data set than has been available in previous analyses (Balaguer and Pernías, 2013; Lado-Sestayo *et al.*, 2020).

Customer delight leads to greater customer loyalty and commitment and generates favourable guest behaviour such as positive word-of-mouth and repeat bookings (Torres and Kline, 2006). Consequently, potential guests will take this delight factor into account when consulting customer ratings to book accommodation. However, the delight factor may be different for each consumer and the scale used by different websites may differ (TripAdvisor's scale ranges from 1–5, while Booking.com's scale is 2.5–10). Jiménez *et al.* (2016) found more than half of hotels (52.56%) had a rating of 4–5 in TripAdvisor, while Mellinas *et al.* (2015) determined 8 is the average rating for Spanish hotels in Booking.com.

The definitions of variables used in this study are shown in Table 1 and the classification of variables and study hypotheses are shown in Figure 1.

Variable	Category of variable	Name of levels	Description	Source
Revenue	Dependent	–	Hotel revenue	Orbis Global Database
Capital	Independent	–	Fixed assets as a proxy of capital (Barros and Santos, 2006)	
Workforce	Independent	–	Number of workers	
Company size	Independent	Small_size Medium_size Large_size	Dummy for each size. The criterion for company size used by Orbis takes into account operating revenue, total assets and number of employees	
Number of hotel star	Independent	3_stars 4_5_stars	In line with Andersson (2010) we included a dummy variable for 4- or 5-star hotels under the assumption that this category is based on superior quality compared to 3-star hotels. 1 or 2-star hotels is the reference category	Booking.com
Consumer rating	Independent	Booking	Dummy variable. 1 represents a rating equal to or greater than 8 and zero otherwise (Mellina *et al.*, 2015)	Booking.com
Location	Independent	Dist_coast (km) Dist_heritage (km) Dist_airport (km)	The Euclidean distance in kilometres. The Spanish airports (managed by AENA) and the sites on the United Nations Educational, Scientific and Cultural Organisation (UNESCO) World Heritage List (National Geographic Institute) were geo-referenced using a GIS	Georeferenced data of hotel location from Orbis Global Database

Table 1.
Definition and source of variables

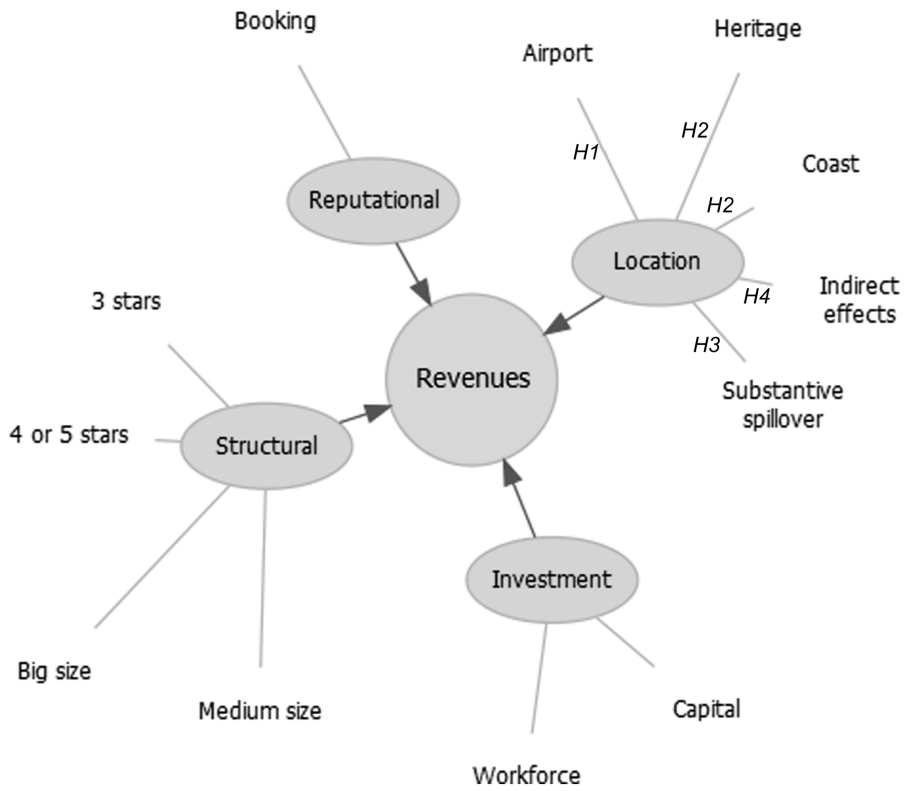

Figure 1.
Classification of variables and study hypotheses

3.2 Methods of analysis

Table 2 shows the descriptive statistics of the variables considered in this study. Even though the average annual revenue of the hotels in the sample is around two million euros, to understand how hotel revenue is related to hotels' accessibility characteristics, we considered, for example, hotels with maximum and minimum revenue.

Variables	Mean	SD	Min	Max
Revenue (€)	2,034,223	3,567,001	77,603	39,771,121
Capital (€1000)	3490.507	10177.390	0.946	144665.600
Workforce (no.)	22.936	35.090	1	453
Medium_Size (binary)	0.522	–	0	1
Large_size (binary)	0.046	–	0	1
Booking (binary)	0.796	–	0	1
3_stars (binary)	0.379	–	0	1
4_5_stars (binary)	0.282	–	0	1
Dist_coast (km)	76.032	119.562	0.001	457.794
Dist_heritage (km)	67.694	49.932	0.156	289.939
Dist_airport (km)	50.452	41.829	0.887	194.515

Table 2.
Descriptive statistics

The maximum revenue (approximately 40 million euros) corresponds to a large 5-star hotel with one of the highest capital investments (136 million euros), a medium to high number of employees (344 employees) and good ratings in Booking.com (9.4). The hotel is located 500 m from the coast in the municipality of Marbella (Malaga). Although it is close to the airport of Torremolinos, it is quite far from the nearest UNESCO monument, the Alhambra in Granada. This particular hotel is surrounded by another 32 hotels (within a radius of 7 km), of which five are large 4-star hotels with mean revenue of 17 million euros. The hotel with the lowest revenue (77,603 euros) is a small 2-star hotel with a capital investment of only 67,000 euros, two employees and good ratings in Booking.com (8.7). This hotel is quite far from the coast but close to the airport and the Pyrenees-Monte-Perdido (UNESCO tourist attraction) and surrounded by another 12 hotels (within a radius of 7 km), of which only two others are small with mean revenue of 327,000 euros.

There are 11 small hotels in the sample which have a very low capital investment of less than 10,000 euros. It should be noted the average number of employees (22.9) is well above the average of most Spanish companies, which is 2 (Barrón, 2016). In our sample, medium-sized hotels abound, accounting for 52% of the total number. Nearly 80% of the hotels have good ratings given that the average rating in Booking.com is 8. It is interesting to note that more than 50% of the hotels are within 12 km from the coast, which confirms Spain's abundant sun, sea and sand hotel offering.

Following the literature review, a Cobb–Douglas model was used in which the response variable hotel revenue and the explanatory variables Workforce and Capital are all in natural logarithms. The coefficients of these variables represent elasticities. For the rest of the continuous variables, the coefficient multiplied by 100 represents the impact on revenue in percentages. However, when the variable is binary, this impact is $100(exp(\beta) - 1)$ (Halvorsen and Palmquist, 1980) where β is the coefficient of the binary variable.

4. Findings

As indicated in the literature review, the spatial accessibility of hotels to points of interest such as the nearest coast, heritage sites and airports might explain differences in hotel revenue. To quantify accessibility, the proximity between locations was measured using the Euclidean distance between hotel location and the nearest point of interest. However, as indicated in the literature review, the effect of distance does not always have to have a monotonically decreasing effect across the plane. In fact, the effect may even disappear after a certain distance, giving rise to a buffer zone or area of influence around the point of interest. In this study, two models were estimated using OLS to explain hotel revenue and determine whether it is better to consider distance or a buffer zone (see Table 4, Mod1.OLS and Mod2.OLS).

4.1 Buffer accessibility variables

In Mod1.OLS (Table 4) accessibility was measured as the Euclidean distance to the points of interest (Dist_coast, Dist_airport and Dist_heritage). All variables in the model are significant at 95% except distance to the coast and to the nearest heritage site. However, Mod2 OLS was estimated considering a buffer zone for each point of interest.

To determine the radius of the buffer zone, the following procedure was used: the first model (Mod1.OLS) was estimated replacing the variables Dist_coast, Dist_airport and Dist_heritage with binary variables that take the value of 1 for a certain distance h (buffer radius). Figure 2 shows the R-squared of the model with the buffer radius, h, from 1 km to 50 km, which increases kilometre by kilometre. The R-squared is maximised for a distance of 40 km to heritage sites, 12 km for the distance to the coast and 23 km for the distance to airports. Figure 3 shows the location of the coast, heritage sites and airports, as well as the buffer zone associated with each of the three points of interest.

4.2 Global spatial dependence

Before analysing the presence of a spatial spillover effect in revenues, it is convenient to analyse the presence of global spatial autocorrelation (dependence) without considering the

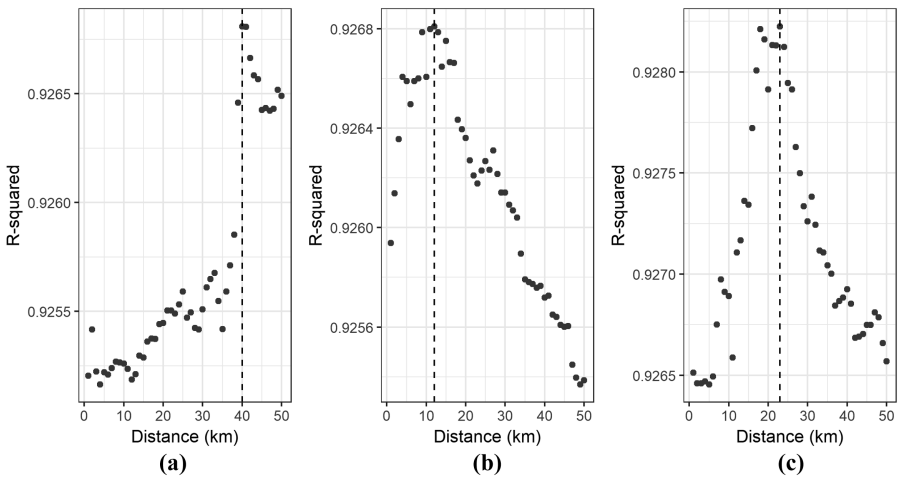

Figure 2.
R-squared for the different distances between each hotel and the point of interest. (a) distance to the nearest heritage site, (b) distance to the coast and (c) distance to the nearest airport

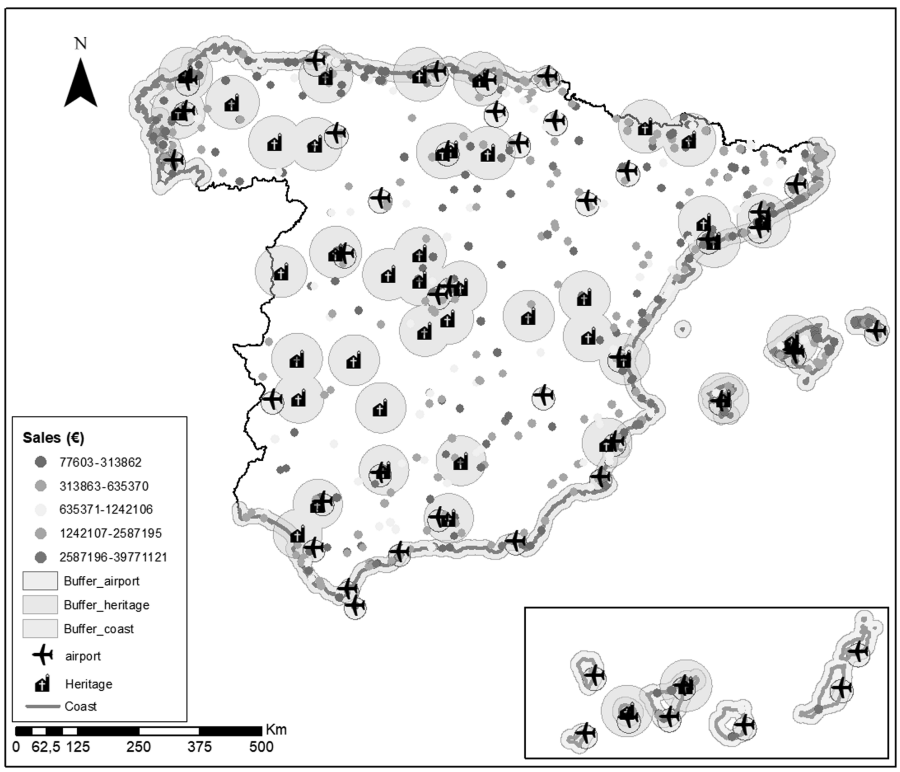

Figure 3.
Location of hotels and hotel revenue in quintiles. Location of airports and UNESCO heritage sites, their buffer zones and coastal buffer zones

possible effect of other explanatory variables. To quantify this global spatial dependence, Moran's I statistic was used (Moran, 1950):

$$I = \frac{n}{\sum_{i-1}^{n}\sum_{j-1}^{n} w_{ij}} \frac{\sum_{i-1}^{n}\sum_{j-1}^{n} w_{ij}(y_{i-}\bar{y})(y_j - \bar{y})}{\sum_{i-1}^{n}(y_{i-}\bar{y})^2} \tag{4}$$

where y_i is the revenue of the i-th hotel, $\bar{y}$ is its mean and w_{ij} are the spatial weights corresponding to hotels i and j. These weights represent the type of neighbourhood and intensity between hotels i and j.

It is important to determine the most suitable specification for the weights w_{ij} (Anselin, 1988). In line with the first law of geography (Tobler, 1970), we have considered the distance between hotels as a measure of proximity between them. Additionally, we have considered three different specifications for the weights w_{ij}: (1) inverse distance, the weight should decrease as the distance between hotels increases; (2) binary, two hotels are considered to be neighbours if they are within an area of influence defined by a radius or threshold and (3) inverse distance with threshold:

$$\begin{aligned} W_1 \text{. Inverse distance}: \; w_{ij} &= \frac{1}{d_{ij}} \\ W_2 \text{. Binary with threshlod}: \; w_{ij} &= \begin{cases} 1 \text{ if } d_{ij} \leq 118.5km \\ 0 \text{ if } d_{ij} > 118.5km \end{cases} \\ W_3 \text{. Inverse distance with threshold}: \; w_{ij} &= \begin{cases} \frac{1}{d_{ij}} \text{ if } d_{ij} \leq 118.5km \\ 0 \quad \text{if } d_{ij} > 118.5km \end{cases} \end{aligned} \tag{5}$$

where d_{ij} is the distance between hotels i and j, and 118.5 km is the threshold. The threshold represents the minimum distance required to avoid excluding hotels.

Table 3 shows the results of Moran's I statistic considering the three specifications for the weights w_{ij}. In all three cases, significant spatial autocorrelation was detected. The degree of persistence in the spatial autocorrelation is a robust indicator that hotel revenue is not randomly distributed across the plane. In contrast, hotels close to other hotels have similar revenue. This leads us to think about the possibility of the presence of the spatial spillover effect.

In this study, three specifications of w_{ij} are significant. In order to select the best one, we need to consider the value of Moran's I statistic (Chi and Zhu, 2008) together with the value of the z-score. In this case, W_1 is the specification that presents the highest value in both Moran's I and the associated z-score. As a result, it was the specification chosen for the study.

Table 3.
Moran's I statistical for revenue with different neighbourhood specifications among hotels

	W_1	W_2	W_3
Moran's I	0.2587	0.1290	0.1945
z-score	10.1070	3.5489	10.6750
p-value	<0.0000	0.0001	<0.0000

Table 4 shows the estimates for the four models considered. Mod1.OLS and Mod2.OLS have been previously discussed. Mod2.SAR and Mod2.SEM represent, respectively, explanatory variables of Mod2, but also consider the substantive spatial spillover effect (SAR model) and spatial autocorrelation in the perturbations or nuisance (SEM model) (Anselin, 1988).

4.3 Models

In line with the Anderson–Darling test (Anderson and Darling, 1954), in Mod1.OLS (AD = 0.6069, $p = 0.1145$) and Mod2. OLS (AD = 0.3679, $p = 0.4297$), the null hypothesis of normality of disturbances is not rejected. Neither of the two models presents problems of multicollinearity given that the variance inflation factor (VIF) does not exceed the value of 5 in any of the cases (2.6678). However, the Moran's *I* error, LM-error, Robust-LM-error, LM-lag and Robust-LM-lag tests reveal the presence of spatial autocorrelation. It should be noted that the value of the LM-lag and Robust-LM-lag statistics are somewhat higher than the LM-error and Robust-LM-error. This indicates the SAR specification is preferred to SEM (Anselin, 1988).

Dependent variable ln_Revenue	Mod1.OLS	Mod2.OLS	Mod2.SAR	Mod2.SEM
const	11.1592 (0.000)	10.9529 (0.000)	9.9316 (0.000)	10.9839 (0.000)
Investment variables				
ln_Workforce	0.7845 (0.000)	0.7830 (0.000)	0.7743 (0.000)	0.7791 (0.000)
ln_Capital	0.0505 (0.000)	0.0500 (0.000)	0.0515 (0.000)	0.0485 (0.000)
Structural variables				
Medium_size	0.3745 (0.000)	0.3584 (0.000)	0.3478 (0.000)	0.3457 (0.000)
Large_size	0.8554 (0.000)	0.8081 (0.000)	0.7644 (0.000)	0.7844 (0.000)
3_stars	0.0690 (0.010)	0.0736 (0.005)	0.0710 (0.005)	0.0795 (0.001)
4_5_stars	0.1752 (0.000)	0.1725 (0.000)	0.1639 (0.000)	0.1786 (0.000)
Reputational				
Booking		0.0665 (0.009)	0.0692 (0.007)	0.0552 (0.030)
Locational variables				
Dist_coast	0.0471 (0.6535)	–	–	–
Dist_heritage	−0.0004 (0.0673)	–	–	–
Dist_airport	−0.0013 (0.000)	–	–	–
Coast_12 km	–	0.1154 (0.000)	0.0833 (0.000)	0.1232 (0.000)
Heritage_40 km	–	0.0769 (0.001)	0.0730 (0.002)	0.0713 (0.010)
Airport_23 km	–	0.1229 (0.000)	0.0934 (0.000)	0.1255 (0.000)
*W*ln_Revenue	–	–	0.0777 (0.000)	–
Wu	–	–	–	0.2101 (0.000)
Goodness of fit				
R-squared	0.9242	0.9282	0.9306	0.9306
AIC	658.183	602.896	572.66	572.97
Spatial autocorrelation				
Moran's *I*	0.1819 (0.000)	0.1548 (0.000)	–	–
LM-error	48.25 (0.000)	34.932 (0.000)	–	–
Robust-LM-error	21.252 (0.000)	16.158 (0.000)	–	–
LM-lag	52.561 (0.000)	35.319 (0.000)	–	–
Robust-LM-lag	25.563 (0.000)	16.546 (0.000)	–	–

Note(s): Dependent variable natural logarithm of revenue. $N = 1015$. *p*-values in brackets. The *R*-squared of Mod2.SAR and Mod2.SEM is the Nagelkerke pseudo *R*-squared

Table 4. Models

The model with the lowest AIC statistic value is Mod2.SAR. Considering this result and the LM and Robust-LM statistics, Mod2.SAR would seem to be the most suitable model for explaining differences in revenue, including the substantive spatial spillover effects.

The significance and signs of the coefficients obtained for Mod2.SAR show that investment (ln_Workforce, ln_Capital), structural (Stars and Size) and reputational (Booking) factors have a significant and positive influence on hotel revenue. Spatial accessibility factors condition revenue through buffer zones that determine the area of influence. Thus, the area of influence of airports is 23 km, the area of influence of UNESCO World Heritage sites is 40 km, and the area of influence to the coast is 12 km. This result empirically supports H1 and H2 and corroborates that the buffer-based ratio better explains hotel revenue than a monotonic distance.

In turn, the coefficient of the variable *W*ln_Revenue is positive and significant. This supports H3, which states that diffusion mechanisms lead to the presence of substantive spillover in the hotel industry.

4.4 Direct, indirect and total spatial spillover effects

According to LeSage and Pace (2009), the so-called direct, indirect and total effects in a SAR model can be obtained by means of the following expression:

$$y = (I - \rho W)^{-1}(X\beta) + \varepsilon$$

$$\begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ \cdot & \cdots & \cdot \\ \frac{\partial E(y_N)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_N)}{\partial x_{Nk}} \end{bmatrix} = (I - \rho W)^{-1} \begin{bmatrix} \beta_k & 0 & \cdots & 0 \\ 0 & \beta_k & \cdots & 0 \\ \cdot & \cdot & \cdots & \cdot \\ 0 & 0 & \cdots & \beta_k \end{bmatrix} \quad (6)$$

where the direct effects are every diagonal element of the partial derivate matrix, and the indirect effects are every off-diagonal element of the matrix. The direct effect represents the impact on revenue of hotel *i* if a certain unit varies in a particular explanatory variable of that hotel.

The indirect effect represents the impact of this explanatory variable on the revenue of neighbouring hotels and is the spatial spillover effect of the explanatory variables (Gong *et al.*, 2014). The total effect is the sum of the direct and indirect effects. Due to feedback effects, the direct effect in the SAR model differs from the OLS coefficient because the impact will spread to neighbouring hotels before returning to the origin (Gong *et al.*, 2014).

The coefficients of models Mod1.OLS, Mod2.OLS and Mod2.SEM for the variables ln_Capital and ln_Workforce represent elasticities, while the other coefficients represent semi-elasticities. Given that the coefficients of Mod2.SAR cannot be directly interpreted, the direct, indirect and total effects were obtained. Table 5 shows the effects of the explanatory variables.

All have the expected signs and are significant at 95%. The variable ln_Workforce can be used as an example to interpret the results in the table. The direct effect of this variable can be understood as follows: if Workforce increases by 1%, then the revenue of hotel *i* will increase by approximately 0.78%. This will lead to an increase of approximately 0.06% in the revenue of its neighbouring hotels (indirect effect). This means that if the hotels (*j*) near hotel *i* invest in Workforce, the revenue of hotel *i* will improve given that it would probably create a market for trained personnel in the proximity of that hotel. Logically, in all cases the direct effect of each predictor is much greater than the indirect effect. The total impact is the sum of both.

Variable	Direct effect	Indirect effect	Total effect
ln_Workforce	0.7759 (0.000)	0.0637 (0.000)	0.8396 (0.000)
ln_Capital	0.0516 (0.000)	0.0042 (0.000)	0.0558 (0.000)
Medium_Size	0.3485 (0.000)	0.0286 (0.000)	0.3771 (0.000)
Large_size	0.7660 (0.000)	0.0629 (0.000)	0.8288 (0.000)
3_stars	0.0712 (0.001)	0.0058 (0.005)	0.0770 (0.001)
4_5_stars	0.1643 (0.000)	0.0135 (0.000)	0.1777 (0.000)
Booking	0.0694 (0.010)	0.0057 (0.027)	0.0751 (0.011)
Coast_12 km	0.0835 (0.000)	0.0069 (0.000)	0.0904 (0.000)
Heritage_40 km	0.0731 (0.005)	0.0060 (0.008)	0.0791 (0.004)
Airport_23 km	0.0936 (0.000)	0.0077 (0.001)	0.1013 (0.000)

Note(s): *p*-values in brackets

Table 5.
Direct, indirect, and total effects

The interpretation of a dichotomous variable such as 4_5_stars would be as follows: if hotel *i* has 4 or 5 stars, its revenue will increase by approximately 17.86% ((exp (0.1643)−1)*100) (direct effect) with respect to a 1- or 2-star hotel and this will indirectly influence the revenue of neighbouring hotels by 1.36% ((exp (0.0135)–1)*100) (indirect effect), thus resulting in a total effect of 19.22%. Hence, in a SAR model it is possible to interpret the indirect effects as the effects of diffusion mechanisms caused by the decisions of neighbouring hotel managers in relation to the explanatory variables. That is, if the manager of a neighbouring hotel (*j*) decides to increase investment in the workforce, this decision will have an indirect effect on the revenues of the hotel (*i*), either by imitating the manager's decision, or learning that this decision can improve revenue or because of competition.

The results obtained from the indirect effects enable us to test hypothesis H4 and indicate that the explanatory factors of a hotel's revenue will affect the revenue of its neighbours likely due to diffusion mechanisms.

5. Conclusion and implications

Similar to previous studies, we have shown that agglomeration externalities influence hotel location decisions (e.g. Canina *et al.*, 2005; Cruz and Teixeira, 2010). Thus, the choice of hotel location constitutes an important factor in hotel performance (Chung and Kalnins, 2001; Tallman *et al.*, 2004). Specifically, our results show that agglomeration economies and policy diffusion play a significant role in hotel industry revenue. While agglomeration economies are related to several factors linked to spatial accessibility, mechanisms of policy diffusion are related to spatial spillover effects. This study showed it is better to use specifications by buffer zones than a monotonically decreasing relationship of distance to the main points of interest to quantify spatial accessibility. This brings the theoretical model closer to the market reality, and these factors should be taken into account in the immediate surroundings when considering the location for a new hotel.

It should be noted that the explanatory variables of proximity to points of interest such as the coast, heritage sites, and airports have a significant positive effect on hotel revenue owing to the area of influence. More specifically, the radius for the area of influence for the coast is 12 km, for UNESCO heritage sites it is 40 km and for airports it is 23 km. In addition, if a hotel is located in an area where there are hotels with high revenue, high investments in productive factors, good structure indicators (size and stars) and good customer ratings, the hotel's revenue will increase.

This study shows accessibility variables produce agglomeration economies because hotels tend to be located closer to each other to obtain benefits from these variables and the hotel's performance increases due to a spillover effect caused by its neighbours (Barros, 2005). Hotels that take advantage of high agglomeration economies tend to have higher survival rates in times

of crisis than hotels located in areas with low agglomeration economies (Luo and Yang, 2013). Moreover, two types of spatial spillover possibly caused by diffusion mechanisms have been observed: endogenous or substantive spillover and indirect effects.

Regarding the structural variables, hotel size and star rating both have the expected signs (Kim *et al.*, 2013). Reputational factors, like customer ratings, have a positive effect on revenue (Öğüt and Onur Taş, 2012). For the investment category, the variables Capital and Workforce have a positive impact on hotel revenue, which is consistent with the literature (Barros, 2004). In addition to having direct effects, investment, structural, and reputational factors have indirect spillover effects on hotel revenue. Consequently, improvements made by a hotel not only have a positive effect on the revenue of that specific hotel, but such investments have a marginal effect on nearby hotels. For example, an improvement in customer ratings of neighbouring hotels will attract more tourists to an area, thus benefiting all the hotels in that area.

The results of this study confirm the four hypotheses proposed and show that location factors have significant effects on hotel revenue in Spain. It has been determined that hotel revenue is affected by both (H1) proximity to means of transport such as airports, and (H2) the classic sun, sea and sand offering, as well as cultural tourist attractions, the two hypotheses related to the presence of agglomeration economies. The study detected substantive spillover where hotel revenue is influenced by the revenue of neighbouring hotels (H3) and indirect effects where hotels benefit from the explanatory variables of the revenue of neighbouring hotels (H4), both of which are caused by mechanisms of diffusion.

We performed a validity test taking into account the direct impact of the COVID-19 health crisis on the tourism industry. Overnight stays were obtained for the second half of 2020 (period in which the lockdown restrictions in Spain were lifted) and 2018 (year of our data) for both domestic and international tourists (INE, 2020). The objective is to compare whether there were significant changes in the visiting preferences of domestic and international tourists in this period, regardless of the absolute number of tourists.

A total of 102 main tourist spots in Spain (municipalities) that account for 76% of hotel rooms in the country were considered and the correlation coefficients were calculated for overnight stays in 2020 and 2018. Comparing both periods, the calculated correlation is 0.92 for domestic tourism and 0.93 for international tourism. This suggests that although tourism indexes have been affected, tourist preferences regarding places to visit remained the same in 2020. Therefore, we assume the results obtained in this research can be extrapolated to the current situation of the industry.

Our findings have implications for the hotel industry, governments and academia. Firstly, they provide relevant information for the hotel industry and shareholders who wish to invest in a new hotel since both the direct and indirect effects of spatial spillover on hotel revenues are quantified. Secondly, the area of influence of factors related to accessibility and hotel revenue have been identified, which can help in making decisions on where to locate new hotels.

The influence of points of interest (areas with high investment in productive factors and infrastructure) on the level of hotel revenue underlines the importance of public and private investment in creating agglomeration economies that generate positive externalities (Chung and Kalnins, 2001; Tallman *et al.*, 2004), the design of urban planning models that fit the desired patterns and enhance the spatial attractiveness of an area (Marco-Lajara *et al.*, 2014), and policies aimed at tourism development (Yang *et al.*, 2014). In addition, this study provides a novel result regarding the fact that diffusion policies create a spillover effect between nearby hotels in terms of revenue (substantive spillover effect) and predictors of revenue (indirect effect).

Moreover, given that the hotel environment is considered natural capital and contributes to hotel resilience, a convenient location will be beneficial for the recovery of the industry after the impacts of COVID-19 (Duarte Alonso *et al.*, 2020). Additionally, the spatial distribution of hotels and their proximity to airports and tourist attractions should be considered in the development of tourism policies to maximise their effectiveness.

Finally, our study supports the theoretical arguments of agglomeration theories which argue that the benefits associated with a higher concentration of competitors improve a firm's revenue. These findings support the positive externalities obtained from the geographic clustering of hotels (Adam and Mensah, 2014; Yang *et al.*, 2014) and is contradictory with the literature that suggests a negative relationship between agglomeration and profitability (Baum and Haveman, 1997; Marco-Lajara *et al.*, 2014). This demonstrates the relevance of working with spatial econometric models to explain hotel industry performance and agglomeration effects in other geographical locations, as well as to clarify the mixed evidence regarding the effects of agglomeration on hotel profitability (Lado-Sestayo *et al.*, 2017).

Despite the importance of our findings and their contributions to the literature, this study has some limitations for future research. Firstly, our theoretical and practical results are of a more general nature, and it would be of interest to conduct research on other geographical areas presenting specific features.

Secondly, although the overall rating of each hotel was used as an indicator of hotel service quality (Nicolau *et al.*, 2020), it does not paint a complete picture of customer satisfaction since all customers do not post their ratings on the website and they cannot be quantified. Therefore, to effectively quantify customer perceptions of hotel service quality, results of ad-hoc measures could be compared to the results obtained using the measure proposed in this research.

Finally, it would be of interest to consider additional variables such as environmental variables (air pollution, noise), policy diffusion mechanisms (learning, financial, or fiscal variables); structural variables (hotel age or refurbishments) and other variables that would justify locating hotels in a specific territory.

References

Adam, I. and Mensah, E. (2014), "Perceived spatial agglomeration effects and hotel location choice", *Anatolia*, Vol. 25 No. 1, pp. 49-60.

Anderson, T. and Darling, D. (1954), "A test of goodness of fit", *Journal of the American Statistical Association*, Vol. 49 No. 268, pp. 765-769.

Anderson, R., Fish, M., Xia, Y. and Michello, F. (1999), "Measuring efficiency in the hotel industry: a stochastic Frontier approach", *International Journal of Hospitality Management*, Vol. 18 No. 1, pp. 45-57.

Andersson, D.E. (2010), "Hotel attributes and hedonic prices: an analysis of internet-based transactions in Singapore's market for hotel rooms", *The Annals of Regional Science*, Vol. 44 No. 2, pp. 229-240.

Anselin, L. (1988), *Spatial Econometrics: Methods and Models*, Kluwer Academic Publishers, Dordrecht.

Arbelo, A., Arbelo-Pérez, M. and Pérez-Gómez, P. (2018), "Estimation of profit efficiency in the hotel industry using a Bayesian stochastic Frontier model", *Cornell Hospitality Quarterly*, Vol. 59 No. 4, pp. 364-375.

Arbia, G., Battisti, M. and Di Vaio, G. (2010), "Institutions and geography: empirical test of spatial growth models for European regions", *Economic Modelling*, Vol. 27 No. 1, pp. 12-21.

Assaf, A.G. (2012), "Benchmarking the Asia Pacific tourism industry: a Bayesian combination of DEA and stochastic Frontier", *Tourism Management*, Vol. 33 No. 5, pp. 1122-1127.

Assaf, A. and Magnini, V. (2012), "Accounting for customer satisfaction in measuring hotel efficiency: evidence from the US hotel industry", *International Journal of Hospitality Management*, Vol. 31 No. 3, pp. 642-647.

Balaguer, J. and Pernías, J. (2013), "Relationship between spatial agglomeration and hotel prices. Evidence from business and tourism consumers", *Tourism Management*, Vol. 36, pp. 391-400.

Barrón, I.D. (2016), "El 94,6% de las empresas españolas tiene de media dos empleados", available at: https://elpais.com/economia/2016/06/28/actualidad/1467111740_869558.html.

Barros, C. (2004), "A stochastic cost Frontier in the Portuguese hotel industry", *Tourism Economics*, Vol. 10 No. 2, pp. 177-192.

Barros, C. (2005), "Evaluating the efficiency of a small hotel chain with a Malmquist productivity index", *International Journal of Tourism Research*, Vol. 7 No. 3, pp. 173-184.

Barros, C.A.P. and Santos, C.A. (2006), "The measurement of efficiency in Portuguese hotels using data envelopment analysis", *Journal of Hospitality and Tourism Research*, Vol. 30 No. 3, pp. 378-400.

Battese, G. (1997), "A note on the estimation of Cobb-Douglas production functions when some explanatory variables have zero values", *Journal of Agricultural Economics*, Vol. 48 Nos 1-3, pp. 250-252.

Baum, J. and Haveman, H. (1997), "Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry 1898-1990", *Administrative Science Quarterly*, Vol. 42 No. 2, pp. 304-338.

Bhanumurthy, K.V. (2002), "Arguing a case for the Cobb-Douglas production function", *Review Commerce Studies*, Delhi, India, Vol. 3, pp. 75-91.

Blal, I. and Sturman, M. (2014), "The differential effects of the quality and quantity of online reviews on hotel room sales", *Cornell Hospitality Quarterly*, Vol. 55 No. 4, pp. 365-375.

Bujosa, A., Riera, A. and Torres, C. (2015), "Valuing tourism demand attributes to guide climate change adaptation measures efficiently: the case of the Spanish domestic travel market", *Tourism Management*, Vol. 47, pp. 233-239.

Canina, L., Enz, C. and Harrison, J. (2005), "Agglomeration effects and strategic orientations: evidence from the US lodging industry", *Academy of Management Journal*, Vol. 48 No. 4, pp. 565-581.

Chen, C. (2007), "Applying the stochastic Frontier approach to measure hotel managerial efficiency in Taiwan", *Tourism Management*, Vol. 28 No. 3, pp. 696-702.

Cheng, D. (2013), "Analyze the hotel industry in porter five competitive forces", *Journal of Global Business Management*, Vol. 9 No. 3, p. 52.

Chi, G. and Zhu, J. (2008), "Spatial regression models for demographic analysis", *Population Research and Policy Review*, Vol. 27 No. 1, pp. 17-42.

Chiang, Y. and Cheng, E. (2014), "Estimating contractors' efficiency with panel data: comparison of the data envelopment analysis, Cobb-Douglas and translog production function methods", *Construction Innovation*, Vol. 14 No. 3, pp. 274-291.

Chica-Olmo, J., Cano-Guervós, R. and Tamaris-Turizo, I. (2019), "Determination of buffer zone for negative externalities: effect on housing prices", *The Geographical Journal*, Vol. 185 No. 2, pp. 222-236.

Chica-Olmo, J., Checa-Olivas, M. and Lopez-Castellano, F. (2021), "Regional characteristics of the gender employment gap: a spatio-temporal approach", *The Economic and Labour Relations Review*. doi: 10.1177/10353046211023242.

Chou, T.-Y., Hsu, C.-L. and Chen, M.-C. (2008), "A fuzzy multicriteria decision model for international tourist hotels location selection", *International Journal of Hospitality Management"*, Vol. 27, pp. 293-301.

Chung, W. and Kalnins, A. (2001), "Agglomeration effects and performance: a test of the Texas lodging industry", *Strategic Management Journal*, Vol. 22 No. 10, pp. 969-988.

Cisneros-Martínez, J. and Fernández-Morales, A. (2015), "Cultural tourism as a tourist segment for reducing seasonality in a coastal area: the case study of Andalusia", *Current Issues in Tourism*, Vol. 18 No. 8, pp. 765-784.

Cruz, S. and Teixeira, A. (2010), "The evolution of the cluster literature: shedding light on the regional studies–regional science debate", *Regional Studies*, Vol. 44 No. 9, pp. 1263-1288.

Deng, Y., Veiga, H. and Wiper, M. (2019), "Efficiency evaluation of hotel chains: a Spanish case study", *SERIEs*, Vol. 10 No. 2, pp. 115-139.

Duarte Alonso, A., Kok, S.K., Bressan, A., O'Shea, M., Sakellarios, N., Koresis, A., Buitrago Solis, M.A. and Santoni, L.J. (2020), "COVID-19, aftermath, impacts, and hospitality firms: an international perspective", *International Journal of Hospitality Management*, Vol. 91, 102654.

Elhorst, J. (2014), *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, Vol. 479, Springer, Heidelberg, p. 480.

Elias-Almeida, A., Miranda, F. and Almeida, P. (2016), "Customer delight: perception of hotel spa consumers", *European Journal of Tourism, Hospitality and Recreation*, Vol. 7 No. 1, pp. 13-20.

Eugenio-Martin, J., Cazorla-Artiles, J. and González-Martel, C. (2019), "On the determinants of Airbnb location and its spatial distribution", *Tourism Economics*, Vol. 25 No. 8, pp. 1224-1244.

Fernandes, M., Santos, S. and Gouveia, A. (2017), "The empirics of agglomeration economies: the link with productivity", *Revue D'économie Industrielle*, Vol. 123 No. 3, pp. 87-109.

Ferreira Neto, A.B. (2021), "The diffusion of cultural district laws across US States", *The Annals of Regional Science*, Vol. 67 No. 1, pp. 189-210.

Gilardi, F. and Wasserfallen, F. (2019), "The politics of policy diffusion", *European Journal of Political Research*, Vol. 58 No. 4, pp. 1245-1256.

Gong, Y., Boelhouwer, P. and de Haan, J. (2014), "Spatial dependence in house prices: evidence from China interurban housing market", *Paper Presented at the ERSA Conference Papers*.

Halvorsen, R. and Palmquist, R. (1980), "The interpretation of dummy variables in semilogarithmic equations", *American Economic Review*, Vol. 70 No. 3, pp. 474-475.

Huete-Alcocer, N., López-Ruiz, V. and Grigorescu, A. (2019), "Measurement of satisfaction in sustainable tourism: a cultural heritage site in Spain", *Sustainability*, Vol. 11 No. 23, p. 6774.

IGN (2020), "Instituto Geográfico Nacional y Asociación Española de Geografía", available at: https://www.ign.es/recursos-educativos/relieve-costa/index.html

INE (2020), "Instituto Nacional de Estadística", available at: https://www.ine.es/

Jiménez, S., Morales, A., de Sandoval, J. and Stefaniak, A. (2016), "Hotel assessment through social media–TripAdvisor as a case study", *Tourism and Management Studies*, Vol. 12 No. 1, pp. 15-24.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V. and Yesiltas, S. (2015), *How to Construct Nationally Representative Firm Level Data from the Orbis Global Database: New Facts and Aggregate Implications*, National Bureau of Economic Research, London.

Kalnins, A. and Chung, W. (2004), "Resource-seeking agglomeration: a study of market entry in the lodging industry", *Strategic Management Journal*, Vol. 25 No. 7, pp. 689-699.

Kim, Y. (2020), "The impact of spatial clustering on the labour productivity of the UK tourism and hospitality industry", Doctoral dissertation, University of Surrey, Guildford.

Kim, W., Cho, M. and Brymer, R. (2013), "Determinants affecting comprehensive property-level hotel performance: the moderating role of hotel type", *International Journal of Hospitality Management*, Vol. 34, pp. 404-412.

Kim, J., Jang, S., Kang, S. and Kim, S. (2020), "Why are hotel room prices different? Exploring spatially varying relationships between room price and hotel attributes", *Journal of Business Research*, Vol. 107, pp. 118-129.

Kim, Y., Williams, A., Park, S. and Chen, J. (2021), "Spatial spillovers of agglomeration economies and productivity in the tourism industry: the case of the UK", *Tourism Management*, Vol. 82, 104201.

Lado-Sestayo, R., Vivel-Búa, M. and Otero-González, L. (2017), "Determinants of TRevPAR: hotel, management and tourist destination", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 12, pp. 3138-3156.

Lado-Sestayo, R., Vivel-Búa, M. and Otero-González, L. (2020), "Connection between hotel location and profitability drivers: an analysis of location-specific effects", *Current Issues in Tourism*, Vol. 23 No. 4, pp. 452-469.

Latinopoulos, D. (2018), "Using a spatial hedonic analysis to evaluate the effect of sea view on hotel prices", *Tourism Management*, Vol. 65, pp. 87-99.

Lee, S. and Jang, S. (2012), "Premium or discount in hotel room rates? The dual effects of a central downtown location", *Cornell Hospitality Quarterly*, Vol. 53 No. 2, pp. 165-173.

LeSage, J.P. and Pace, R.K. (2009), *Introduction to Spatial Econometrics*, Taylor & Francis Group, Boca Raton.

Lionetti, S. (2009), "Tourism productivity: incentives and obstacles to fostering growth", *Tourism Analysis*, Vol. 14 No. 6, pp. 781-791.

Luo, H. and Yang, Y. (2013), "Spatial pattern of hotel distribution in China", *Tourism and Hospitality Research*, Vol. 13 No. 1, pp. 3-15.

Luo, H. and Yang, Y. (2016), "Intra-metropolitan location choice of star-rated and non-rated budget hotels: the role of agglomeration economies", *International Journal of Hospitality Management*, Vol. 59, pp. 72-83.

Marco-Lajara, B., Claver-Cortés, E. and Úbeda-García, M. (2014), "Business agglomeration in tourist districts and hotel performance", *International Journal of Contemporary Hospitality Management*, Vol. 26 No. 8, pp. 1312-1340.

Martin-Fuentes, E. (2016), "Are guests of the same opinion as the hotel star-rate classification system?", *Journal of Hospitality and Tourism Management*, Vol. 29, pp. 126-134.

Martín-Rivero, R., Ledesma-Rodríguez, F. and Lorenzo-Alegría, R. (2021), "Technical efficiency and agglomeration economies in the hotel industry: evidence from canary islands", *Applied Spatial Analysis and Policy*, Vol. 14 No. 4, pp. 777-793.

Martins, F., Silva, F., Rocha, C., Queiroz, M. and Araújo, C. (2012), "Analysis of efficiency of the regulated transportation coach operator by stochastic Frontier of Cobb-Douglas and translog functions: the case of the interstate passenger coach transportation in Brazil", *Journal of Transport Literature*, Vol. 6 No. 3, pp. 08-33.

Mellinas, J., Martínez, S. and Bernal, J. (2015), "Booking. com: the unexpected scoring system", *Tourism Management*, Vol. 49, pp. 72-74.

Montant, G. (2020), "The determinants of the hotel sector revenues: the case of French Polynesia", *Tourism Economics*, Vol. 26 No. 5, pp. 809-829.

Moran, P. (1950), "Notes on continuous stochastic phenomena", *Biometrika*, Vol. 37 Nos 1/2, pp. 17-23.

Myles Shaver, J. and Flyer, F. (2000), "Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States", *Strategic Management Journal*, Vol. 21 No. 12, pp. 1175-1193.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al Jabir, A., Iosifidis, C. and Agha, R. (2020), "The socio-economic implications of the Coronavirus and COVID-19 pandemic: a Review", *International Journal of Surgery*, Vol. 78, pp. 185-193.

Nicolau, J., Mellinas, J. and Martín-Fuentes, E. (2020), "Satisfaction measures with monetary and non-monetary components: hotel's overall scores", *International Journal of Hospitality Management*, Vol. 87, 102497.

Öğüt, H. and Onur-Taş, B. (2012), "The influence of internet customer reviews on the online sales and prices in hotel industry", *The Service Industries Journal*, Vol. 32 No. 2, pp. 197-214.

Pavelescu, F. (2011), "Some aspects of the translog production function estimation", *Romanian Journal of Economics*, Vol. 32 No. 1, p. 41.

Pawlicz, A. and Napierala, T. (2017), "The determinants of hotel room rates: an analysis of the hotel industry in Warsaw, Poland", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 1, pp. 571-588.

Pérez-Rodríguez, J. and Acosta-González, E. (2007), "Cost efficiency of the lodging industry in the tourist destination of Gran Canaria (Spain)", *Tourism Management*, Vol. 28 No. 4, pp. 993-1005.

Porter, M. (1998), *Clusters and the New Economics of Competition*, Harvard Business Review, Boston, Vol. 76.

Reynes, F. (2017), *The Cobb-Douglas Function as a Flexible Function: Analysing the Sustitution Between Capital, Labor and Energy*, Sciences Po, No. 2017-12.

Rigall-I-Torrent, R. and Fluvià, M. (2011), "Managing tourism products and destinations embedding public good components: a hedonic approach", *Tourism Management*, Vol. 32 No. 2, pp. 244-255.

Roehl, W. and Van-Doren, C. (1990), "Locational characteristics of American resort hotels", *Journal of Cultural Geography*, Vol. 11 No. 1, pp. 71-83.

Shaw, G. and Williams, A. (2009), "Knowledge transfer and management in tourism organisations: an emerging research agenda", *Tourism Management*, Vol. 30 No. 3, pp. 325-335.

Shipan, C. and Volden, C. (2008), "The mechanisms of policy diffusion", *American Journal of Political Science*, Vol. 52 No. 4, pp. 840-857.

Skrede, O. and Tveteraas, S. (2019), "Cruise spillovers to hotels and restaurants", *Tourism Economics*, Vol. 25 No. 8, pp. 1286-1301.

Soloaga, I. (1999), "The treatment of non-essential inputs in a Cobb-Douglas technology: an application to Mexican rural household-level data", available at: SSRN 632569.

Tallman, S., Jenkins, M., Henry, N. and Pinch, S. (2004), "Knowledge, clusters, and competitive advantage", *Academy of Management Review*, Vol. 29 No. 2, pp. 258-271.

Thrane, C. (2007), "Examining the determinants of room rates for hotels in capital cities: the Oslo experience", *Journal of Revenue and Pricing Management*, Vol. 5 No. 4, pp. 315-323.

Tobler, W. (1970), "A computer movie simulating urban growth in the Detroit region", *Economic Geography*, Vol. 46, pp. 234-240.

Torres, E. and Kline, S. (2006), "From satisfaction to delight: a model for the hotel industry", *International Journal of Contemporary Hospitality Management*, Vol. 18 No. 4, pp. 290-301.

UNESCO (2020), "United Nations Educational, scientific and cultural Organization", available at: http://whc.unesco.org/en/statesparties/es/

UNWTO (2019a), "World Tourism Organization", *European Union Tourism Trends*, available at: https://www.e-unwto.org/doi/pdf/10.18111/9789284419470

UNWTO (2019b), "The World Tourism Organization", *Panorama del turismo internacional*, available at: https://www.e-unwto.org/doi/pdf/10.18111/9789284421237

Valentin, M. and O'Neill, J. (2019), "The value of location for urban hotels", *Cornell Hospitality Quarterly*, Vol. 60 No. 1, pp. 5-24.

Viladecans-Marsal, E. (2004), "Agglomeration economies and industrial location: city-level evidence", *Journal of Economic Geography*, Vol. 4 No. 5, pp. 565-582.

Vives, A. and Jacob, M. (2020), "Dynamic pricing for online hotel demand: the case of resort hotels in Majorca", *Journal of Vacation Marketing*, Vol. 26 No. 2, pp. 268-283.

Wang, S., Chen, Y., Huang, J., Chen, N. and Lu, Y. (2019), "Macrolevel traffic crash analysis: a spatial econometric model approach", *Mathematical Problems in Engineering*, Vol. 2019, pp. 1-10.

Wannakrairoj, W. and Velu, C. (2021), "Productivity growth and business model innovation", *Economics Letters*, Vol. 199, 109679.

Weidenfeld, A., Williams, A. and Butler, R. (2010), "Knowledge transfer and innovation among attractions", *Annals of Tourism Research*, Vol. 37 No. 3, pp. 604-626.

White, P. and Mulligan, G. (2002), "Hedonic estimates of lodging rates in the four corners region", *The Professional Geographer*, Vol. 54 No. 4, pp. 533-543.

Yang, Y., Wong, K. and Wang, T. (2012), "How do hotels choose their location? Evidence from hotels in Beijing", *International Journal of Hospitality Management*, Vol. 31, pp. 675-685.

Yang, Y., Luo, H. and Law, R. (2014), "Theoretical, empirical, and operational models in hotel location research", *International Journal of Hospitality Management*, Vol. 36, pp. 209-220.

Yang, Y., Mao, Z. and Tang, J. (2018), "Understanding guest satisfaction with urban hotel location", *Journal of Travel Research*, Vol. 57, pp. 243-259.

Zhang, G., Wang, R. and Cheng, M. (2020), "Peer-to-peer accommodation experience: a Chinese cultural perspective", *Tourism Management Perspectives*, Vol. 33, 100621.

Zhou, K., Liu, H. and Wang, Q. (2019), "The impact of economic agglomeration on water pollutant emissions from the perspective of spatial spillover effects", *Journal of Geographical Sciences*, Vol. 29 No. 12, pp. 2015-2030.

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The directional spillover effects and time-frequency nexus between stock markets, cryptocurrency, and investor sentiment during the COVID-19 pandemic

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Received 25 September 2022
Revised 15 January 2023
16 February 2023
28 February 2023
Accepted 3 March 2023

Abstract

Purpose – This paper aims to analyze the connectedness between Gulf Cooperation Council (GCC) stock market index and cryptocurrencies. It investigates the relevant impact of RavenPack COVID sentiment on the dynamic of stock market indices and conventional cryptocurrencies as well as their Islamic counterparts during the onset of the COVID-19 crisis.

Design/methodology/approach – The authors rely on the methodology of Diebold and Yilmaz (2012, 2014) to construct network-associated measures. Then, the wavelet coherence model was applied to explore co-movements between GCC stock markets, cryptocurrencies and RavenPack COVID sentiment. As a robustness check, the authors used the time-frequency connectedness developed by Barunik and Krehlik (2018) to verify the direction and scale connectedness among these markets.

Findings – The results illustrate the effect of COVID-19 on all cryptocurrency markets. The time variations of stock returns display stylized fact tails and volatility clustering for all return series. This stressful period increased investor pessimism and fears and generated negative emotions. The findings also highlight a high spillover of shocks between RavenPack COVID sentiment, Islamic and conventional stock return indices and cryptocurrencies. In addition, we find that RavenPack COVID sentiment is the main net transmitter of shocks for all conventional market indices and that most Islamic indices and cryptocurrencies are net receivers.

Practical implications – This study provides two main types of implications: On the one hand, it helps fund managers adjust the risk exposure of their portfolio by including stocks that significantly respond to COVID-19 sentiment and those that do not. On the other hand, the volatility mechanism and investor sentiment can be interesting for investors as it allows them to consider the dynamics of each market and thus optimize the asset portfolio allocation.

Originality/value – This finding suggests that the RavenPack COVID sentiment is a net transmitter of shocks. It is considered a prominent channel of shock spillovers during the health crisis, which confirms the behavioral contagion. This study also identifies the contribution of particular interest to fund managers and investors. In fact, it helps them design their portfolio strategy accordingly.

Keywords Cryptocurrencies, RavenPack COVID sentiment, COVID-19 pandemic,
Diebold–Yilmaz spillover index, Wavelet coherence

Paper type Research paper

The authors would like to thank the editor for his careful reading and comments. The authors declare no conflict of interest.

European Journal of Management and Business Economics
Vol. 34 No. 1, 2025
pp. 23-46
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-09-2022-0305

1. Introduction

The COVID-19 pandemic is not only a health crisis. It also poses a growing threat to the fragile Chinese and global financial markets, which have faced tremendous uncertainties during this period. It differs from other crises in its broad impact and distributional consequences. Indeed, it is hitting already stagnant and fragile economies in the Middle East and North Africa (MENA) with lockdowns, disrupted supply chains, dramatic declines in tourism revenues and labor remittances and temporarily low oil prices (Alaoui Mdaghri *et al.*, 2021; Bani-Khalaf and Taspinar, 2022; Mehdi *et al.*, 2022).

Indeed, over the past two decades, shocks and crises transmitted to financial markets have led to structural changes in the volatility of cryptocurrencies. This has prompted investors to examine the interconnectivity, risk transfer and hedging strategies between the financial markets and cryptocurrencies. In fact, cryptocurrencies have received substantial attention from the public, in general, and investors and researchers, in particular. Specifically, the launch of cryptocurrencies in the MENA region is expected to have a significant impact on the economic and financial system of the region. Thus, the low cost and security of virtual transactions highlight the importance of this electronic payment method and its significant role in the financial system of the MENA region (Sayed and Abbas, 2018). Therefore, understanding the impact of the cryptocurrency market as one of the determinants of Gulf Cooperation Council (GCC) stock market returns is crucial.

For instance, several recent research studies focused on the impact of COVID–19 on financial markets in general and financial assets, such as cryptocurrencies and gold, in particular (Corbet *et al.*, 2020; Zhang *et al.*, 2020). In fact, Zhang *et al.* (2020) conclude that the instability and economic damage caused by the pandemic made the financial market highly unpredictable and volatile. In addition, Al-Awadhi *et al.* (2020) state that the daily growth of total cases and deaths negatively correlates with the stock market performance. In fact, investors' expectations of risk and return have changed, leading them to reallocate their portfolios. Although some studies have examined the relationship between cryptocurrencies and financial markets, many have been limited many to a single country (Al-Awadhi *et al.*, 2020; Narayan *et al.*, 2020) or have used it an international sample without considering the issue of connectivity (Bouri *et al.*, 2021). The gap in existing research motivated us to investigate the shock transmission between RavenPack COVID sentiment, GCC financial stock market and cryptocurrencies during the COVID-19 pandemic.

To the best of our knowledge, this study is the first to conduct a formal and robust empirical investigation of the impact of COVID-19 on the volatility interconnection between the RavenPack COVID sentiment, the GCC financial market, and, particularly, the Islamic and conventional cryptocurrencies. To achieve this goal, we examine spillover effects between these variables using the VAR-based spillover index approach from the generalized VAR framework introduced by Diebold and Yilmaz (2012). This method identifies the directional connectedness perspective. It also measures the levels of this connectedness, i.e. total connectedness, total directional connectedness, and pairwise directional connectedness from one variable to another. Additionally, we apply wavelet coherence to examine the co-movements between these variables in a joint time-frequency domain. This technique was proposed to improve the accuracy of financial time series forecasting, which can provide a matrix to accommodate the correlation at each time and frequency point. This advantage allows us to observe the change in consistency between GCC stock market returns, cryptocurrency returns and RavenPack COVID sentiment.

The paper is therefore organized as follows: Section 2 reviews recent research relevant to our study. Section 3 describes the applied methodology in detail. Section 4 introduces the data and our preliminary analyses. In section 5, we reveal and discuss the main empirical results achieved in this research. Finally, the last section concludes the paper.

2. Literature review

The COVID-19 pandemic has been one of the most economically costly pandemics in recent history. In fact, Ashraf (2021) shows that the decline in stock returns as a response to the increasing number of confirmed cases is greater in countries whose investors have higher domestic uncertainty aversion. For their part, Liu *et al.* (2021) indicate that COVID-19 increases the risk of stock market crashes in China. More precisely, financial markets continue to experience a downward trend worldwide due to investors' lack of interest in riskier assets and have lost nearly $3 trillion since the start of the pandemic (Forbes, 2020). In fact, the COVID-19 crisis differs from other crises because of its broad impacts and distributional consequences. It is clear that the MENA region will not be the same after this pandemic. Indeed, the economic impacts are felt the most: financial markets collapse, tourists evaporate due to flight bans and closures, and oil prices drop. With the UAE canceling its Expo 2020 and Saudi Arabia banning the annual hajj pilgrimage, both states have lost hundreds of millions of dollars. In fact, the UAE was expected to attract 25mn visitors to its Expo 2020 in October 2020, and Saudi Arabia used to receive 20mn religious pilgrims each year (Ng, 2020). Meanwhile, Egypt is losing about $1bn per month in lost tourist revenue (Bianco and Wildangel, 2020). Indeed, the pandemic has depressed the oil price as demand dries up. Like global markets, GCC markets have also been trending downward by an average of 20% since the reporting of the first case of COVID-19 in the UAE. Investors continue to lose daily due to the declining market trend. In March 2020, investors in Dubai, Abu Dhabi, Saudi Arabia, Kuwait and Qatar lost nearly $6bn, $8.3bn, $41bn, $2.8bn and $11.9bn, respectively, in a single day (Khaleej Times, 2020).One of the most affected sectors in the UAE is real estate, with Chinese businessmen being the main investors in real estate projects in Dubai (Ng, 2020). As China recovers from the effects of the pandemic, many Chinese investors remain reluctant to make new transactions. Even before the epidemic, the UAE faced an economic catastrophe due to the Dubai bubble (Solomon, 2020).In addition, Qatar's stock markets are also suffering from the impact of COVID-19, including the oil and gas, financial services, real estate and telecommunication stock markets, which have collapsed despite a 10bn Rial stimulus package for the stock market (KPMG, 2020).

The pandemic disrupted businesses and caused unprecedented fluctuations in commodity prices, resulting in a 21 and 6.15% decline in the stock markets of Bahrain and Kuwait, respectively (KPMG, 2020). The The World Bank Economic Update (2020) indicates that Oman's economy will also remain under stress as the oil and gas, banking, tourism and logistics sectors are in a deficit. Likewise, Mensi *et al.* (2020) examine the impacts of COVID-19 on the multifractality of gold and oil prices under upward and downward trends. They show strong evidence of asymmetric multifractality that increases with a rising fractality scale. Moreover, multifractality is particularly higher in the downtrend (uptrend) for Brent oil (gold). This excess asymmetry increased during the COVID-19 outbreak. Akhtaruzzaman *et al.* (2021) also examine the way financial contagion occurs across financial and non-financial firms between China and G7 countries during COVID-19. Their empirical results show that financial and non-financial listed firms in these countries experience a significant increase in conditional correlations between their stock returns. However, there is little industry-level research on the effect of COVID-19 on cryptocurrency prices in the existing literature. There are also several industry limitations at the economic level of COVID-19 (Yang *et al.*, 2016; Bouri *et al.*, 2019; Gomes and Gubareva, 2021).

These studies on the interdependence of foreign exchange and cryptocurrency markets are attracting considerable research interest from a contagion perspective. Specifically, the COVID-19 crisis has negatively influenced the potential role of cryptocurrencies as diversified investments (Tiwari *et al.*, 2019; Gil-Alana *et al.*, 2020).Therefore, studying the dynamics of fiat currencies and cryptocurrencies through the COVID-19 bear market and its initial recovery can be beneficial. It offers a unique opportunity to examine the economic

impact of this pandemic on the financial system and its stability as a whole. In fact, joint dynamics of conventional currencies, such as EUR, GBP and RMB, and major cryptocurrencies have been explored recently (e.g. Kristjanpoller and Bouri, 2019).Therefore, analyzing the behavior of cryptocurrencies relative to major fiat currencies is recommended. In fact, it helps to assess the potential ability of cryptocurrencies to serve as a hedging medium for fiat currencies in times of global crisis, such as the COVID-19 pandemic turmoil.

Recently, Fakhfekh and Jeribi (2020) have focused on modeling the volatility dynamics of cryptocurrencies. However, few studies have investigated volatility transmission between Bitcoin and other cryptocurrencies (Katsiampa *et al.*, 2019; Beneki *et al.*, 2019). Indeed, Agosto and Cafferata (2020) study the relationship between the explosive behaviors of cryptocurrencies using a unit root test approach. They prove a strong interdependence in the cryptocurrency market (as Corbet *et al.*, 2018 and Yi *et al.*, 2018).In this context, Aslanidis *et al.* (2019) examine the conditional correlations between four cryptocurrencies (Bitcoin, Monero, Dash and Ripple), the S&P 500, bonds and gold. They show that the studied cryptocurrencies are highly correlated. However, the association between cryptocurrencies and conventional financial assets is negligible.

Using a copula-ADCC-EGARCH model, Tiwari *et al.* (2019) investigate the time-varying correlations between six cryptocurrencies and the S&P 500 index markets. They state that the overall time-varying correlations are very low, which indicates that cryptocurrencies serve as a hedging asset against the risk of the S&P 500 stock market. They also show that volatilities respond more to a negative than a positive shock in both markets. In addition, they identify Litecoin as the most effective hedging asset against S&P 500 risk. As a result, they conclude that cryptocurrency might be one of the most important elements in portfolio diversification. Furthermore, Charfeddine *et al.* (2020) study the dynamic relationship between Bitcoin and Ethereum and major commodities and financial stocks. They confirm that these two cryptocurrencies can be ideal for financial diversification. More interestingly, Banerjee *et al.* (2022) find that COVID-19 news sentiment influences cryptocurrency returns. In fact, unlike previous results, the link is unidirectional between news sentiment and cryptocurrency returns. Indeed, Ozdamar *et al.* (2022) attest that retail (institutional) investor attention has a negative (positive) effect on cryptocurrency returns. Moreover, retail (institutional) investor attention aggravates (constrains) idiosyncratic risk while both types of attention boost cryptocurrency market liquidity.

Unlike traditional cryptocurrencies, Islamic cryptocurrencies are supported by quantifiable financial fundamentals that maintain their value. They are new technical applications that leverage existing blockchains to meet the religious requirements of some investors. The most common cryptocurrencies that comply with Islamic laws are X8X, HelloGold and OneGram (Lahmiri and Bekiros, 2019). These are based on gold, which is one of six "Rabawi" commodities approved by Muslim investors. For those seeking to satisfy religious needs, investing in these emerging innovations is an intriguing proposition. Nevertheless, there is little investigation into the dynamics of Islamic and conventional cryptocurrencies during the health crisis (Mnif *et al.*, 2020). To fill this gap in the existing literature, this study aims to examine the relevant impact of RavenPack COVID sentiment on the dynamics of stock market indices and conventional cryptocurrencies as well as their Islamic counterparts during the onset of the COVID-19 crisis.

3. Methodological approach

This study aims to examine the impact of RavenPack COVID sentiment on the dynamics of conventional and Islamic stock indices, as well as cryptocurrencies, during the onset of the COVID-19 crisis. It analyzes the correlation between these variables over the health crisis

period. For our modeling objective, we use a two-step methodology: First, in order to analyze the spillover effect between investor sentiment proxies and stock market return, we start with the methodology proposed by Diebold and Yilmaz (2012). More precisely, we apply Diebold and Yilmaz's connectedness index to quantify the static and dynamic connectedness of investor sentiment and financial markets during the COVID-19 crisis. Second, we use the wavelet coherence model to explore the co-movements between these variables for different time frequencies.

3.1 The directional spillover model

In this research, we explore the co-movement between the RavenPack COVID sentiment and conventional and Islamic stock indices, as well as cryptocurrencies, using the spillover index approach developed by Diebold and Yilmaz (2012). In fact, total, directional and net spillovers can all be identified using this approach. Indeed, the DY model is based on the vector autoregressive VAR model (Pesaran and Shin, 1998), which is described as follows:

$$y_t = \sum_{i=1}^{P} \pi_i y_{t-i} + \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim i.id \sim (0, \sum)$, π_i contains $N \times N$ matrix of regression parameters, ε_t is the vector of identically and independently distributed errors with $\sum$ being their variance-covariance matrix.

The VAR (p) model can therefore be written as follows:

$$y_t = \sum_{i=0}^{\infty} \theta_i \varepsilon_{t-i} \tag{2}$$

$$\theta_i = \pi_1 \theta_{i-1} + \pi_2 \theta_{i-2} + \ldots + \pi_p \theta_{i-p} \tag{3}$$

where θ_i is the N × N matrix of moving average coefficients and θ_0 provides an N × N identity matrix and $\theta_i = 0 \forall i < 0$.

According to Pesaran and Shin (1998), the H-step-ahead forecast-error variance decomposition is expressed as follows:

$$d_{ij}^{g}(H) = \frac{\partial_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \pi_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \pi_h' \sum e_i\right)^2} \tag{4}$$

The square root of the diagonal elements of the variance-covariance matrix is represented by ∂_{jj}. In the VAR model, the shocks to each variable are not orthogonal, i.e. they are different from one of the sums of own and cross-variance of the variables in each row of the variance decomposition matrix. As a result, the elements of the decomposition matrix are normalized:

$$\check{d}_{ij}^{g}(H) = \frac{d_{jj}^{g}(H)}{\sum_{j=1}^{N} d_{ij}^{g}(H)} \tag{5}$$

with, $\sum_{j=1}^{N} \widetilde{d}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{d}_{ij}^{g}(H) = N$.

In fact, the normalized elements of the decomposition matrix in equation (6) can be used to generate a total spillover (TS). Furthermore, we can calculate the directional and net spillover (NS) as follows:

$$TS^{g}(H) = \frac{\sum i,j=1 \, \widetilde{d}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{d}_{ij}^{g}(H)} \times 100 = \frac{\sum i,j=1 \, \widetilde{d}_{ij}^{g}(H)}{N} \times 100 \tag{6}$$

$$\text{With}: DS^{g}_{i\leftarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{d}^{\,g}_{ji}(H)}{N} \times 100 \tag{7}$$

$$DS^{g}_{i\leftarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{d}^{\,g}_{ji}(H)}{N} \times 100 \tag{8}$$

$$NS^{g}_{i}(H) = DS^{g}_{i\leftarrow j}(H) - DS^{g}_{i\leftarrow j}(H) \tag{9}$$

Then, the average contribution of the shock spillovers across the variables to the total forecast error variance is measured by the TS index. In fact, the DS in equation (7) estimates the spillover effects from all other markets j to market i for $i \# j$. However, the DS in equation (8) measures the spillover effects from market i to all other markets j.

Moreover, we should note that equations (7) and (8) are used to calculate NS to identify the variables as senders or receivers of net shocks. Therefore, when NS is negative, market i is a net receiver of spillover effects. However, a positive value of NS indicates that spillover effects originate from market i to all other markets (net transmitter).

3.2 The wavelet coherence model

The continuous wavelet decomposition model is used to identify the multi-horizon nature of the co-movement between RavenPack COVID sentiment, conventional and Islamic index returns and cryptocurrencies. It allows us to illustrate the evolution of local correlations over time and frequency. Thus, a red area at the top (bottom) of the graph denotes a strong correlation at high (low) frequency, while a red area on the left (right) implies a strong correlation at the beginning (end) of the sample period. For two-time series $x(t)$ and $y(t)$, the wavelet-squared coherence, similar to Fourier's analysis, is defined as the absolute squared value of the smoothed cross-wavelet spectrum, which is normalized by the power spectrum of the smoothed wavelets:

$$R^2(\tau, s) = \frac{\left|S(s^{-1}W_{x,y}(\tau, s))\right|^2}{|S(s^{-1}W_y(\tau, s))||S(s^{-1}W_y(\tau, s))|} \tag{10}$$

where: S denotes a smoothing operator in time and scale. Since the theoretical distributions of wavelet coherence are unknown, the 5% statistical significance level is determined using Monte Carlo Simulation. We can use the wavelet-squared coherence to measure the traditional correlation of two-time series in time and scale. As a result, the wavelet squared coherence coefficient $R^2(\tau, s)$ is between 0 and 1, with a high (low) dependence value representing a strong (weak) co-movement. By observing the wavelet squared coherence graph, we can detect regions in time-frequency space where the two-time series move together and particularly capture both time- and frequency-varying co-movement features (Grinsted *et al.*, 2004; Rua and Nunes, 2009; Dewandaru *et al.*, 2014).

4. Data and preliminary analysis

4.1 Data

In this study, we use daily and monthly price data from the GCC stock market indices, the RavenPack COVID sentiment, and the six major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) and their Islamic counterparts X8X Token (X8X), Halalchain (HLC), and HelloGold (HGT). Closing prices were obtained from Datastream and CoinMarketCap [1]. We choose these cryptocurrencies based on their market capitalization and availability. The conventional cryptocurrencies, Bitcoin, Ethereum, and Ripple (XRP), have the largest market capitalization. On the other hand, Halalchain, HelloGold, and X8X have been certifiedas

Islamic compliant. The study period is from January 1, 2018, to December 21, 2022. We consider two sub-periods: the pre-crisis period (January 1, 2018, to November 30, 2019) and the COVID-19 period (December 2, 2019, to December 21, 2022). The daily return is calculated as follows:

$$RET_t = lnP_t - lnP_{t-1} \tag{11}$$

where: P_t and P_{t-1} denote the closing price of the GCC stock index or cryptocurrencies at time t and t–1, respectively. Following Forbes and Rigobon (2002) and Akhtaruzzaman and Shamsuddin (2016), closing prices are recorded in local currencies. Furthermore, Mink (2015) argues that it would be more appropriate to use returns denominated in local currency than those in a common currency (e.g. returns denominated in US dollars). This is because only returns denominated in local currency accurately reflect price fluctuations in national stock markets. However, returns converted into a common currency reflect exchange rate fluctuations.

Therefore, RavenPack COVID sentiment is a new indicator to measure the GCC investor sentiment from December 2, 2019, to December 21, 2022. We obtain data for RavenPack COVID sentiment from the RavenPack database [2].

4.2 Preliminary analysis

Table 1 presents the descriptive statistics of conventional and Islamic returns for the six financial markets (Panel A and Panel B, respectively) and the six cryptocurrencies (Panel C). In fact, for all periods studied, a closer look at this table shows a positive average for most conventional and Islamic stock returns, except Bahrain and Oman. All conventional and Islamic monthly return series show excess kurtosis. Moreover, for both skewness and kurtosis measures, the results of the Jarque–Bera normality test reject the null hypothesis of normal distribution. However, during the COVID-19 shock period, RavenPack's COVID sentiment showed negative average returns. We also notice that the conventional cryptocurrency (Bitcoin) has the lowest risk. However, Islamic cryptocurrencies (Halachain, HelloGold and X8X_Token) register the highest risk with standard deviations of 0.247641, 0.277908, and 0.245447, respectively. According to the skewness and kurtosis indicators, as well as the Jarque–Bera test, all series significantly deviate from the normal distribution.

Figures 1 and 2 illustrate the evolution of the GCC stock market and cryptocurrency returns from January 1, 2018, to December 21, 2022. After extreme volatility starting in December 2019, the GCC stock market index declined significantly. Indeed, since the global spread of COVID-19, panic has prevailed in the financial markets. As a result, several markets around the world continued to fall. Moreover, according to Figure 2, cryptocurrency returns show high fluctuations. In fact, the impact of COVID-19 is observed in all cryptocurrency markets. The time variations in stock returns display stylized fact tails and volatility clustering for all return series. This stressful period increased investor pessimism and fears and generated negative emotions. As a result, it drove investors to sell their shares and exit the stock market. Interestingly, this behavior further amplified the deterioration of the GCC financial market.

5. Empirical results and discussion

5.1 The spillover structure between the RavenPack COVID sentiment and financial market index returns

In this section, we refer to the spillover index approach developed by Diebold and Yilmaz (2012) to explore the co-movement between the RavenPack COVID sentiment and

Full sample: From January 1, 2018 to December 21, 2022						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
Panel A: Conventional index returns						
Mean	0.000394	0.000361	7.59E-06	0.000162	0.000370	0.000592
Max	0.034233	0.061446	0.027620	0.048530	0.068315	0.080762
Min	−0.060006	−0.293565	−0.057350	−0.102077	−0.086846	−0.084063
St. D	0.005030	0.011395	0.004988	0.008520	0.009450	0.010264
Sk	−1.587710	−11.05766	−0.827988	−0.983397	−1.384840	−0.363630
Kur	22.46852	262.1617	15.72638	17.40558	16.40645	19.39977
JB	29409.98	5113504	12448.80	15977.49	14164.61	20368.30
Panel B: Islamic index returns						
Mean	−0.000150	0.000355	−0.000129	5.07E-05	0.000197	0.000299
Max	0.088677	0.056758	0.030007	0.050791	0.078117	0.076350
Min	−0.082752	−0.111291	−0.049481	−0.099417	−0.081500	−0.100405
St. D	0.010707	0.008769	0.005990	0.007829	0.008873	0.009846
Sk	−0.215506	−2.989991	−0.579469	−1.025973	−1.293249	−1.281378
Kur	15.66093	43.09163	12.32175	21.45611	20.07758	27.37355
JB	12063.12	123506.3	6632.572	25920.37	22424.74	45147.92
	BITCOIN	ETHEREUM	XPR	HALALCHAIN	HELLOGOLD	X8X_TOKEN
Panel C: Cryptocurrencies returns						
Mean	0.001895	0.002206	0.001247	−0.002094	−0.000811	0.014790
Max	0.176044	0.219405	0.423353	1.966510	4.009822	2.773463
Min	−0.433714	−0.563071	−0.549549	−1.618760	−4.543656	−1.971844
St. D	0.038626	0.0524499	0.062193	0.186324	0.302688	0.235321
Sk	−1.215413	−1.367350	0.045004	0.102793	−0.906739	3.030687
Kur	19.14438	17.26383	17.96167	30.01108	115.3699	50.32298
JB	12461.20	9861.226	10465.44	34110.71	590466.0	106412.6
COVID-19 health crisis period (from December 2, 2019 to December 21, 2022)						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
Panel A: Conventional index returns						
Mean	0.000335	0.000284	0.000195	0.000156	0.000362	0.000588
Max	0.034233	0.061446	0.027620	0.034106	0.068315	0.080762
Min	−0.060006	−0.116340	−0.057350	−0.102077	−0.086846	−0.084063
St. D	0.005670	0.010529	0.005407	0.008492	0.010034	0.011523
Sk	−1.830149	−3.264765	−1.121334	−1.727672	−1.794459	−0.452809
Kur	22.00037	39.45543	17.57530	24.42590	18.98901	19.09522
JB	17425.74	63838.11	10121.37	21921.52	12497.78	12095.07
Panel B: Islamic index returns						
Mean	8.76E-05	0.000323	−3.08E-06	3.84E-05	0.000258	0.000650
Max	0.088677	0.056758	0.030007	0.036374	0.078117	0.076350
Min	−0.082752	−0.111291	−0.049481	−0.099417	−0.081500	−0.100405
St. D	0.010497	0.010201	0.006427	0.007762	0.009562	0.011435
Sk	0.002146	−3.078752	−0.716844	−1.842290	−1.616923	−1.379493
Kur	21.54297	37.79873	13.16410	29.39142	21.97256	23.85981
JB	15888.35	57708.03	4868.715	32811.77	17116.29	20458.44
Panel C: RavenPack COVID sentiment						
Mean	−2.315216	−2.205838	−3.495595	−2.025324	−6.980351	−8.204676
Max	11.50000	15.36000	19.40000	23.39000	20.78000	17.89000
Min	−23.23000	−27.94000	−30.04000	−33.85000	−51.29000	−45.21000

Table 1.
Descriptive statistics

(*continued*)

COVID-19 health crisis period (from December 2, 2019 to December 21, 2022)						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
St. D	4.791915	5.928783	6.010876	6.105490	10.77691	10.53742
Sk	−0.663279	−0.774372	−0.699203	−0.875094	−0.782618	−0.705348
Kur	4.746236	4.869607	5.268650	6.228517	4.425496	3.426449
JB	148.2805	181.7328	218.9880	415.8330	138.1951	66.96756
	BITCOIN	ETHEREUM	XPR	HALACHAIN	HELLOGOLD	X8X_TOKEN
Panel D: Cryptocurrencies returns						
Mean	0.002969	0.004639	0.001554	0.000321	0.002115	0.025222
Max	0.176044	0.219405	0.423353	1.966510	3.681385	2.773463
Min	−0.433714	−0.563071	−0.549549	−1.618760	−3.689977	−1.971844
St. D	0.039801	0.054248	0.065894	0.247641	0.277908	0.245447
Sk	−2.202687	−2.141302	−0.575578	0.011170	0.003367	2.822560
Kur	29.43642	25.91587	20.90638	19.12190	114.1190	40.32355
JB	33430.48	25294.36	14984.73	12096.94	574670.4	66317.92

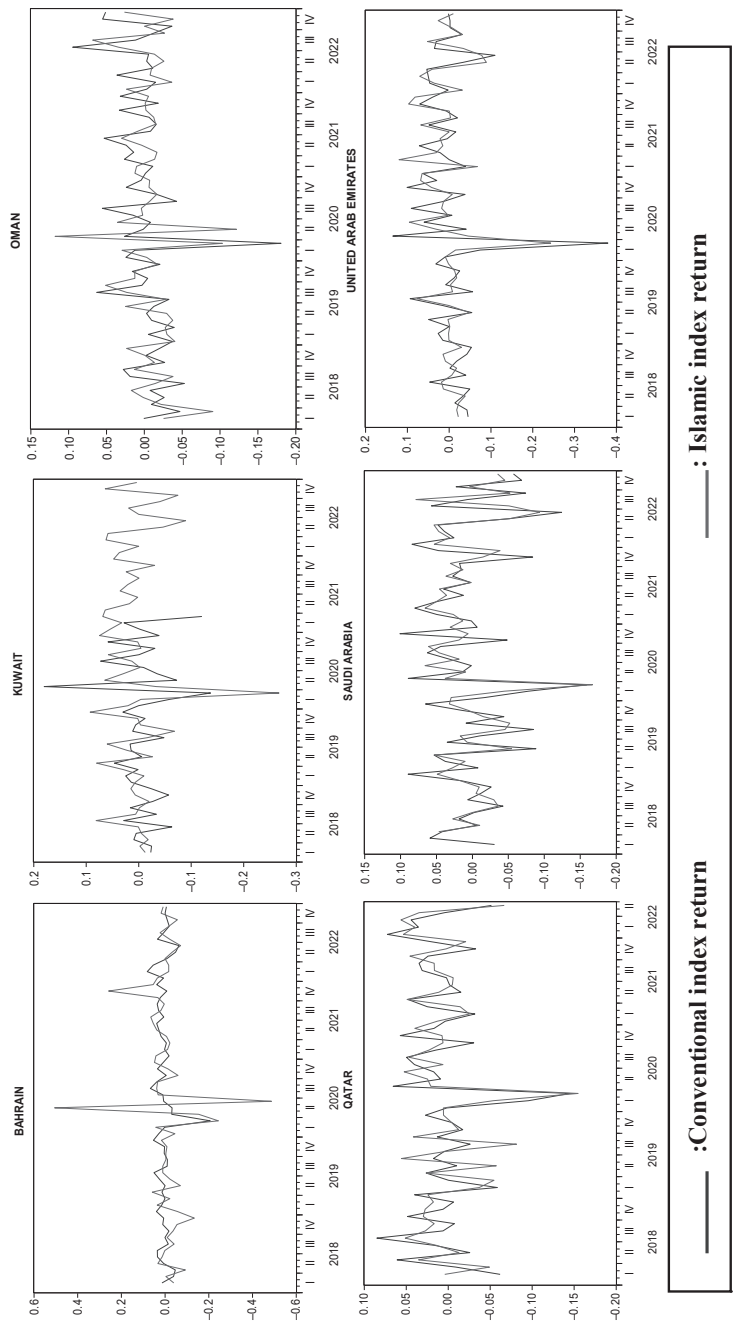
Note(s): Max: maximum, Min: minimum, St. D: standard deviation, Sk:skewness, Kur:kurtosis, JB:Jarque–Bera
Source(s): Authors' calculations

Table 1.

conventional and Islamic stock indices, as well as cryptocurrencies. In fact, Table 2 displays the total volatility spillovers calculated for the health crisis period. For each country, the ij th entry represents the estimated contribution to the forecast error variance of index *i* from innovations in index *j*. For example, we learn from Bahrain that innovations to the RavenPack COVID sentiment are responsible for 1.1%, 0.5%, 0.2% and 1.8% of the variance in the forecast error of conventional and Islamic index returns, Bitcoin and X8X-token, respectively. However, innovations inconventional and Islamic index returns, Bitcoin and X8X-token are responsible for 0.4%, 0.1%, 0.2% and 0.2% of the variance in the forecast error of RavenPack COVID sentiment, respectively.

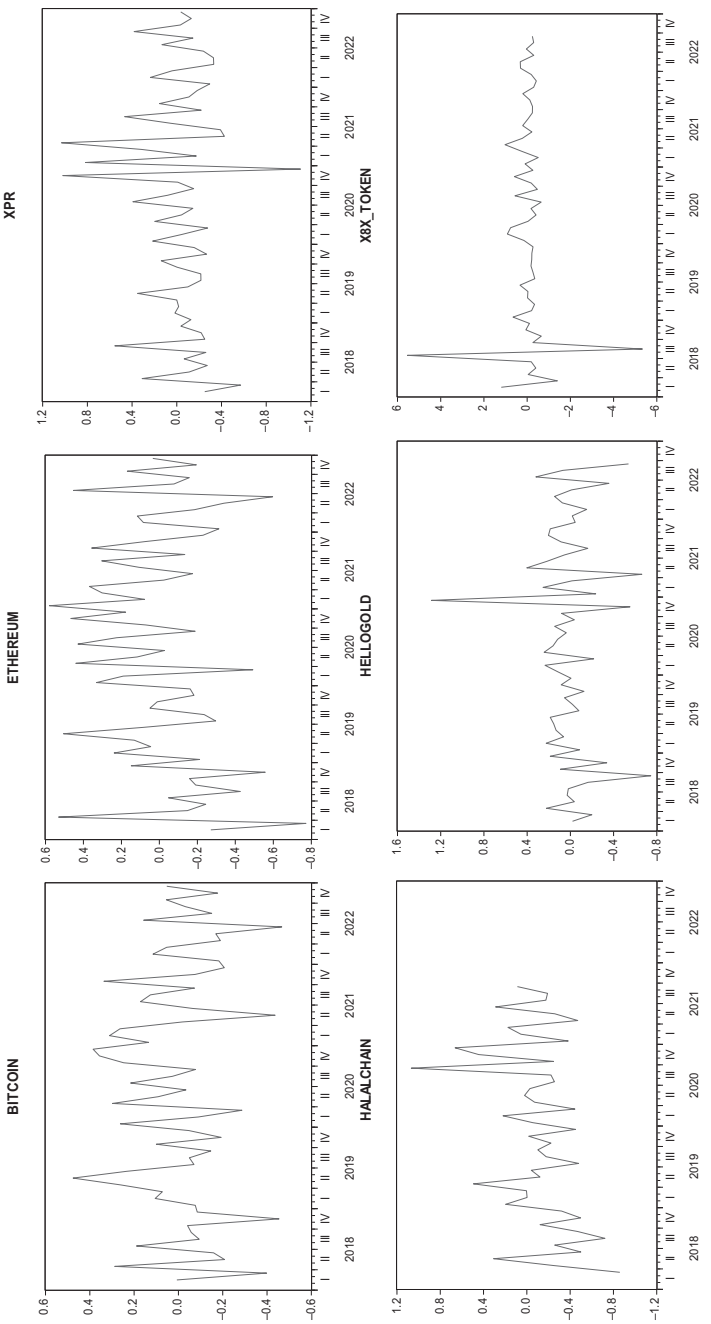
Directional spillovers (DSs) to others capture the spillover effects directed from index *i* to all other indices. Similarly, DSs from others report the spillover effects received by index i from all other indices. Analyzing Table 2 and focusing on Bahrain, we note that the total volatility spillovers from RavenPack COVID sentiment to others (i.e. contributions from RavenPack COVID sentiment to others) are larger than the total volatility spillovers from others to RavenPack COVID sentiment (i.e. RavenPack COVID sentiment contributions from others).This result indicates that volatility spillover is higher from RavenPack COVID sentiment to returns. This result is similar to Oman and the UAE. In fact, they exhibit higher DS from RavenPack COVID sentiments to others than the total volatility spillover from index returns to RavenPack COVID sentiment. More precisely, by analyzing the direction of spillover (NS's row) in Table 2, we find that RavenPack COVID sentiments are the primary transmitters of net shock for all conventional market indices.

On the other hand, the majority of Islamic indices and cryptocurrencies are net receivers. This finding demonstrates the critical role of the RavenPack COVID sentiment shock on conventional indices. Moreover, the TS index is quite high. Indeed, it rises from 5.7% to 16.5% in all Islamic and conventional index markets. Thus, these results report a high shock spillover between the RavenPack COVID sentiment, the Islamic and conventional stock return indices and cryptocurrencies.



Source(s): Authors' elaborations

Figure 1.
Time series plot of returns of the stock markets



Source(s): Authors' elaborations

Figure 2.
Time series plot of returns of the cryptocurrency markets

Table 2. Directional spillover indexes (%) between RavenPack COVID sentiment and conventional and Islamic stock markets, index and cryptocurrencies returns

			Bahrain From							Kuwait From				
To	Sentba	ret_bac	ret_bai	ret_btc	ret_x8x-token	From others	To	Sentkw	ret_kwc	ret_kwi	ret_btc	ret_x8x_token	From others
sentba	99	0.4	0.1	0.2	0.2	1	sentkw	95.8	0.5	1.8	1.4	0.5	4.2
ret_bac	1.1	95.8	1.7	1.1	0.3	4.2	ret_kwc	0.5	90	7.9	1.4	0.3	10
ret_bai	0.5	11	87.4	0.9	0.3	12.6	ret_kwi	0.4	52.6	45	1.7	0.3	55
ret_btc	0.2	4.7	0.9	93.6	0.6	6.4	ret_btc	1.1	2.2	0.5	95.6	0.6	4.4
ret_x8x-token	1.8	0.7	0.7	1	95.8	4.2	ret_x8x_token	1.1	0.2	0.2	1	97.4	2.6
Contribution to Others	3.6	16.8	3.4	3.3	1.4	28.4	Contribution to Others	3.1	55.5	10.4	5.5	1.8	76.2
Net contribution (To - From)	2.6	12.6	−9.2	−3.1	−2.8	Total Connectedness 5.7%	Net contribution (To - From)	−1.1	45.5	−44.6	1.1	−0.8	Total Connectedness 15.2%
Conclusion	Net transmitter	Net transmitter	Net recipient	Net recipient		Net recipient	Conclusion	Net recipient	Net transmitter	Net recipient	Net transmitter		Net recipient

			Oman From							Qatar From				
To	Sentom	ret_omc	ret_omi	ret_btc	ret_x8x_token	From others	To	Sentqa	ret_qac	ret_qai	ret_btc	ret_x8x_token	From others
sentom	98.8	0.1	0.1	0.7	0.3	1.2	Sentqa	96.8	1.1	1.7	0.2	0.2	3.2
ret_omc	0.8	97.2	0.9	1	0.2	2.8	ret_qac	0.2	97.3	0.9	1	0.5	2.7
ret_omi	2.4	20.6	76.2	0.6	0.2	23.8	ret_qai	0.3	35.9	63.2	0.4	0.3	36.8
ret_btc	0.3	2.3	1.6	95.1	0.7	4.9	ret_btc	0.5	1.8	1.9	95.1	0.8	4.9
ret_x8x_token	0.7	0.3	0.6	0.9	97.5	2.5	ret_x8x_token	0.4	0.7	0.2	1.1	97.5	2.5

(*continued*)

Table 2.

	Oman From						Qatar From					
To	Sentom	ret_omc	ret_omi	ret_btc	ret_x8x_token	From others	Sentqa	ret_qac	ret_qai	ret_btc	ret_x8x_token	From others
Contribution to Others	4.2	23.4	3.2	3.1	1.4	35.3	1.4	39.5	4.7	2.7	1.8	50.1
Net contribution (To - From)	3	20.6	−20.6	−1.8	−1.1	Total Connectedness 7.1%	−1.8	36.8	−32.1	−2.2	−0.7	Total Connectedness 10%
Conclusion	Net transmitter	Net transmitter	Net recipient	Net recipient		Net recipient	Net recipient	Net transmitter	Net recipient	Net recipient		Net recipient

	SaudiArabia From						United Arab Emirates From					
To	Sentsa	ret_sac	ret_sai	ret_btc	ret_x8x_token	From others	Sentuae	ret_uaec	ret_uaei	ret_btc	ret_x8x_token	From others
Sentsa	94.9	3.8	0.1	1	0.3	5.1	sentuae	97.7	0.7	0.9	0.5	0.3	2.3
ret_sac	0.3	84.7	13.7	1.1	0.2	15.3	ret_uaec	1.4	95	1.3	2.1	0.2	5
ret_sai	0.6	53.3	45.2	0.6	0.3	54.8	ret_uaei	1.2	31.6	66.3	0.8	0.1	33.7
ret_btc	0.9	1.8	2.1	94.6	0.7	5.4	ret_btc	0.3	2.1	0.9	96	0.7	4
ret_x8x_token	0.5	0.1	0.2	1	98.2	1.8	ret_x8x_token	0.3	0.2	0.1	1.1	98.4	1.7
Contribution to Others	2.2	58.9	16.1	3.8	1.4	82.4	Contribution to Others	3.1	34.6	3.2	4.4	1.4	46.8
Net contribution (To - From)	−2.9	43.6	−38.7	−1.6	−0.4	Total Connectedness 16.5%	Net contribution (To - From)	0.8	29.6	−30.5	0.4	−0.3	Total Connectedness 9.4%
Conclusion	Net recipient	Net transmitter	Net recipient	Net recipient		Net recipient	Conclusion	Net transmitter	Net transmitter	Net recipient	Net transmitter		Net recipient

Source(s): Authors' calculations

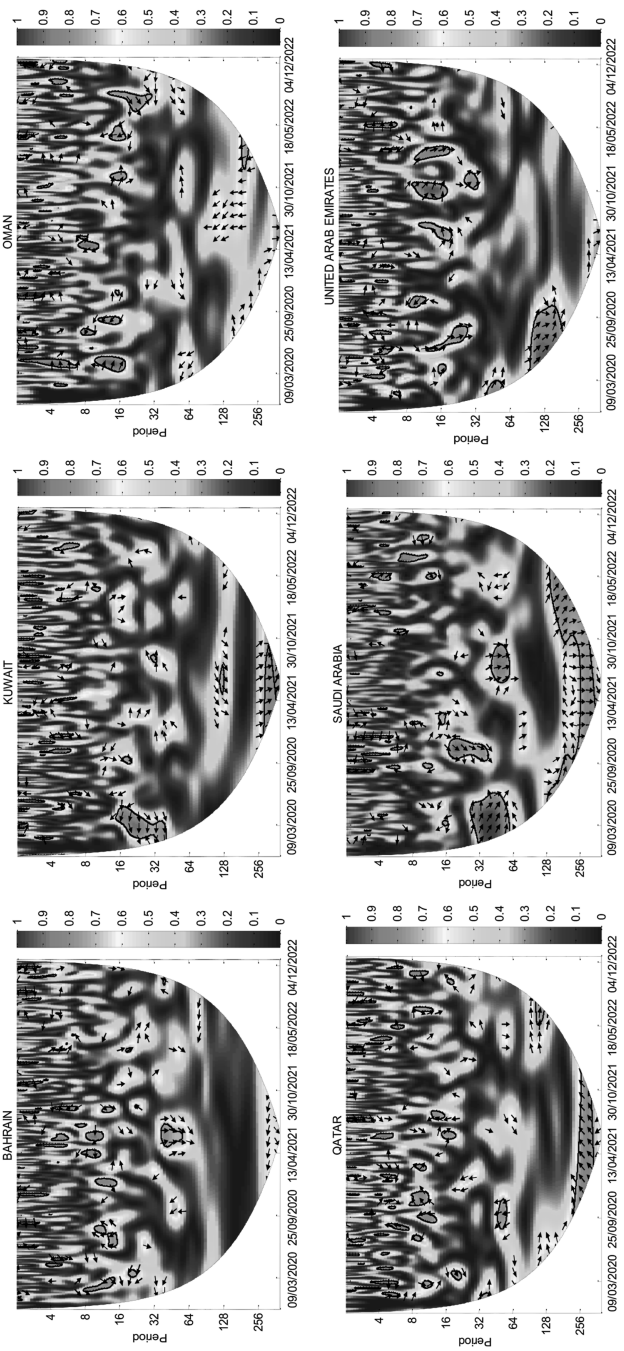
Therefore, we conclude that shocks from the RavenPack sentiment index are transmitted to the Islamic and conventional market indices.They are also transferred to cryptocurrencies corroborating the predictive power of the RavenPack COVID sentiment as it transmits the shock to the financial markets and shows a lead effect. This result supports Soltani and Boujelbene Abbes (2022), who find a significant peak of connectivity between investor sentiment and Chinese stock market return during the turmoil periods of 2015–2016 and late 2019–2020. Interestingly, the information on shock receivers and transmitters is useful in predicting potential portfolio risk and helping investors make appropriate adjustments to their portfolios. Indeed, it greatly improves their investment decisions.

5.2 RavenPack COVID sentiment and the market index returns: lead or lag effect

Using wavelet coherence, we can distinguish the short-and long-term co-movement dynamics between RavenPack COVID sentiment, conventional and Islamic index returns, and cryptocurrencies. Figures 3–5 represent the estimated wavelet coherence between the RavenPack investor index and conventional index returns, between RavenPack COVID sentiment and Islamic index returns, and between the RavenPack investor index and cryptocurrency returns, respectively. Furthermore, we can determine the significance level of wavelet coherence based on Monte Carlo simulations. The vertical axis presents the scale, whereas the horizontal axis indicates the time intervals. The blue (red) colored area shows weak (strong) co-movement at high and low frequencies. Arrows pointing to the right (→) signify that the variables are in phase (cyclical effect on each other). (↗) implies that the investors' index is leading. (↘) indicates that investors' index is lagging. Arrows pointing to the left (←) mean that the variables are out of phase (countercyclical effect). (↖) shows that investors' index is lagging. Finally, (↙) means that investors' sentiments are leading.

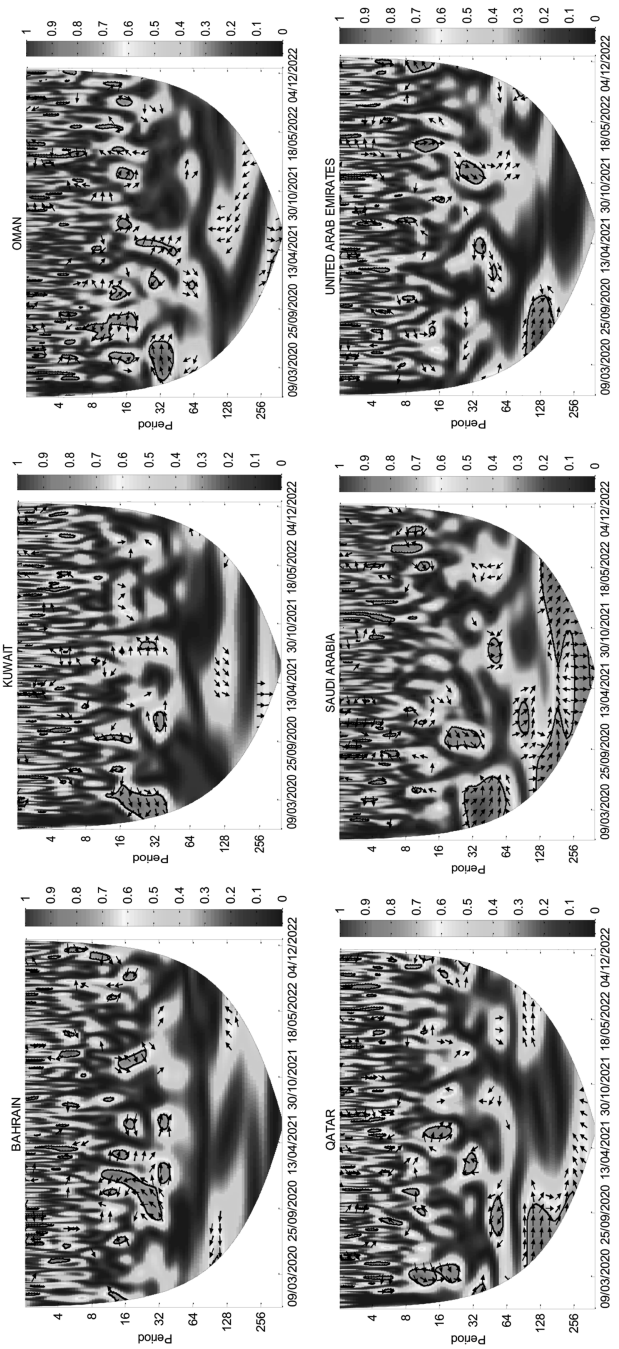
The analyzed figures exhibit a significant correlation at both the high and low-frequency time scales during the period 2020–2022, with large islands of dark colors scattered along the 4–256 days bands. This correlation is much higher for Saudi Arabia, Qatar and the UAE. This result can be explained by the fact that the financial markets have experienced significant fluctuations. These have significantly affected the investor's emotions, leading to the volatility of the market index. An exception is the Islamic index of Saudi Arabia, with a higher power taking place in July 2020 and coinciding with the fear of another outbreak of COVID-19. All five cryptocurrencies, and to a lower extent Ethereum, show additional power on the 4–128 days scale in the August to September period, i.e. the middle of the second COVID-19 wave.

We study the consistency and phase between the RavenPack COVID sentiment and the market indices. The results show that the connectedness between RavenPack COVID sentiment and conventional and Islamic markets and cryptocurrencies depends on the market under consideration and the investment horizons. Moreover, the arrow analysis indicates that during the COVID-19 pandemic, RavenPack COVID sentiment and conventional and Islamic index returns are in phase for frequencies between 32 and 128 months. The arrows pointing to the right and upwards mean that RavenPack COVID sentiment is the "leader" in the sense that it drives returns toward a high correlation for most indices. However, comparing the density of the red dots, the Bahrain conventional index and Ethereum seem the least affected by RavenPack COVID sentiment. For cryptocurrencies and Islamic indices, we observe a highly significant correlation in the July–August period, which is mostly counter cyclical. In this same period, the correlation is positive (right-turning arrows) for the X8X Token. For the 64–128 days bands, the conventional indices of Bahrain and Kuwait, and Ethereum are not more affected by RavenPack COVID sentiment. This suggests that these markets can serve as a safe haven during a pandemic.



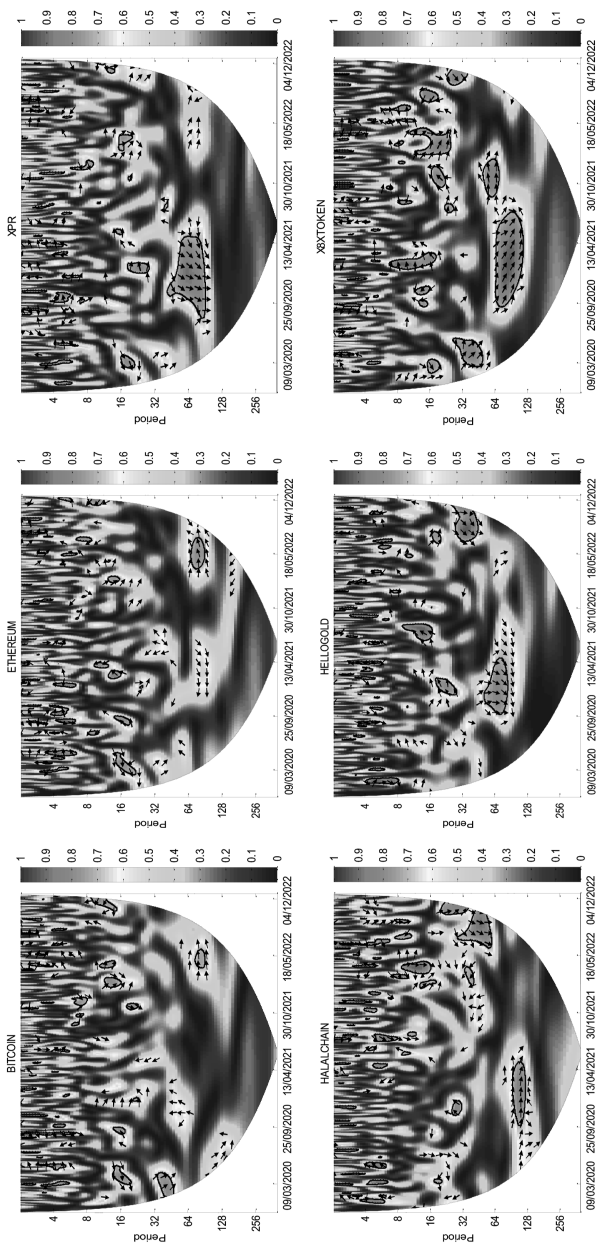
Source(s): Authors' elaborations

Figure 3.
Correlation between RavenPack COVID sentiment and conventional index returns



Source(s): Authors' elaborations

Figure 4.
Correlation between RavenPack COVID sentiment and Islamic index returns



Source(s): Authors' elaborations

Figure 5.
Correlation between RavenPack COVID sentiment and Cryptocurrencies

Although counterintuitive, this positive consistency between RavenPack COVID sentiment and the long-run financial and cryptocurrency markets is in line with the findings of Goodell and Goutte (2021) and Sharif *et al.* (2020). The difference in results regarding the investment horizon reflects the differences in perception between short-term and longer-term investors. Several studies have acknowledged that risk can decrease significantly if the asset is held for a longer period (Butler and Domian, 1991). In our case, long-term investors seem to be insulated from the short-term market fluctuations induced by the fear of COVID-19. This result confirms the severe effect of the COVID-19 pandemic on the financial markets during the study period. For instance, digital currencies can serve as a store of value during periods of market turbulence. Indeed, they also represent a source of portfolio diversification. In this context, Gil-Alana *et al.* (2020) identify that cryptocurrencies can be an important diversification option for investors, mainly Bitcoin and Ethereum.

Omane-Adjepong and Alagidede (2019) prove that all diversification benefits within cryptocurrencies are most commonly found in intra-week to intra-month time horizons for specific market pairs. However, the level of inter-market connectivity and volatility links are identified as sensitive to both liquidity and volatility. Additionally, Liu (2019) provides evidence that portfolio diversification across different cryptocurrencies can significantly improve investment outcomes. When specifically examining the market relationships between cryptocurrencies and other conventional financial variables, Bouri *et al.* (2017) find that Bitcoin is a poor hedge and only suitable for diversification purposes. This finding is echoed when examining the S&P500 exchange (Tiwari *et al.*, 2019), Eurostoxx 50, Nikkei 225 and CSI 300 (Feng *et al.*, 2018).

6. Robustness check

In order to verify the robustness of our empirical findings, we apply the time-frequency connectedness developed by Baruník and Křehlík (2018) to check the direction and scale connectedness among these markets. Specifically, we decompose the connectedness into two different frequency bands: the short and long terms, corresponding to about one–four days and more than 10 days, respectively.

Figure 6 plots the total volatility connectedness during a 100-month rolling window as the predictive horizon for the underlying decomposition. The total volatility connectedness depicts long-run fluctuations rather than short-run ones over the entire period. The total volatility connectedness peaked during the COVID-19 health crisis. It increased sharply in 2020 from 20% to 45%, which suggests that strong connectedness mainly happens in the long term. In addition, since the second half of 2020, when the pandemic was widespread, total connectedness has increased again, reaching a historical peak (45% for Saudi Arabia) in March 2020. Moreover, the TS index evolves abruptly, suggesting the existence of major shocks lowering connectivity between different GCC markets.

7. Conclusion

The COVID-19 pandemic has become a serious threat to the GCC and global economies. Given the unknown pathways of its spread and virulence, which created huge recovery and earning opportunities, it is difficult to assess its severity. Furthermore, identifying the connectedness between the Gulf Council Cooperation (GCC) stock market index and six cryptocurrencies is essential for effective risk management and portfolio diversification. Thus, in order to extend the existing literature in this field, this article mainly investigated the shock transmission between RavenPack COVID sentiment, the GCC stock market, and cryptocurrencies during the health crisis period.

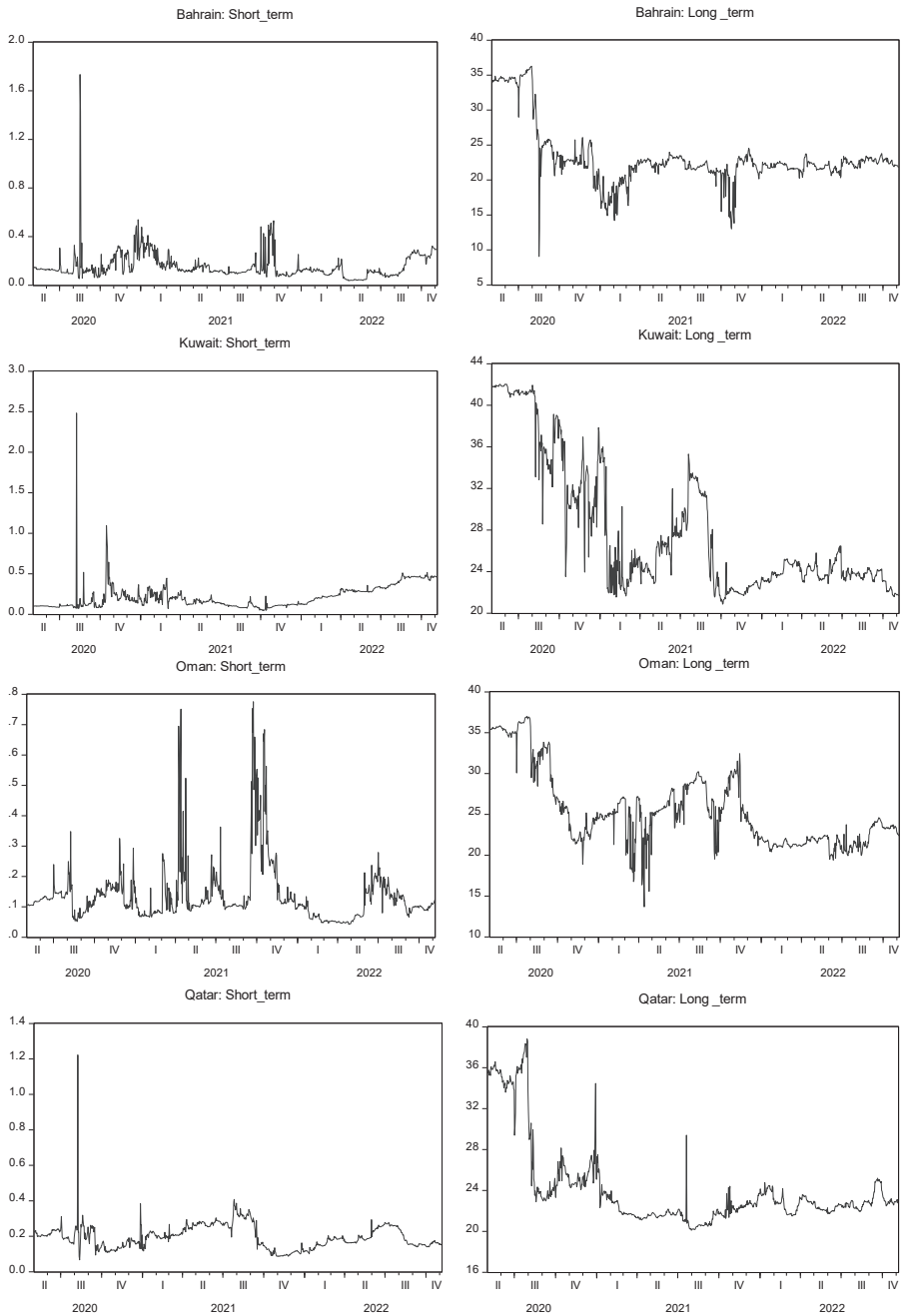


Figure 6.
Dynamic frequency connectedness of the RavenPack COVID sentiment and conventional and Islamic stock markets index and cryptocurrencies returns

(*continued*)

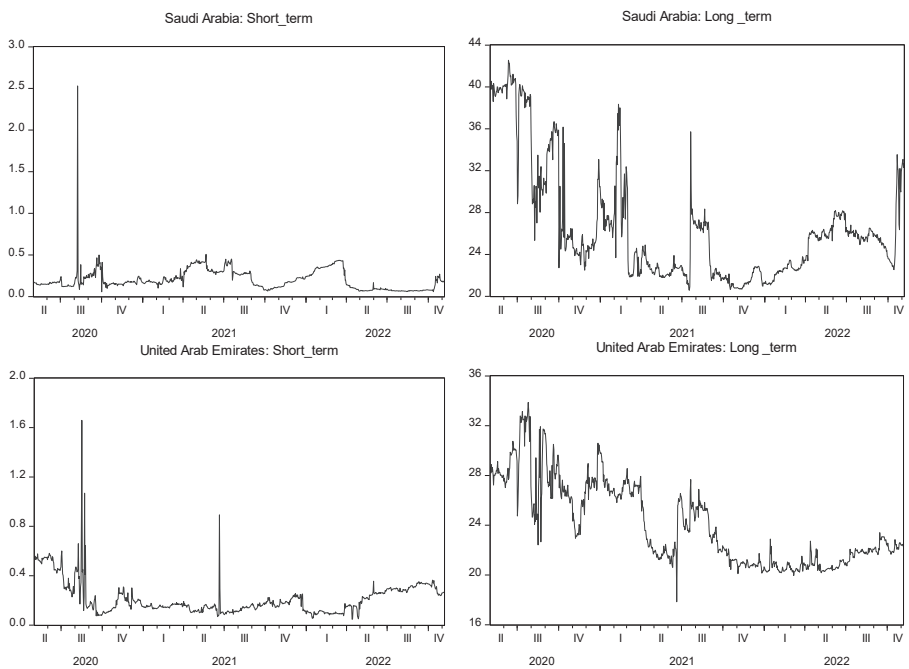


Figure 6.

Source(s): Authors' elaborations

Moreover, we relied on the methodology of Diebold and Yilmaz (2012, 2014) to construct network-associated measures. Then, the wavelet coherence model was applied to explore the co-movements between GCC stock markets, cryptocurrencies and RavenPack COVID sentiment. In order to check the robustness of our results, we employed the time-frequency connectedness developed by Baruník and Křehlík (2018). In fact, our empirical analysis illustrates the effect of COVID-19 on all cryptocurrency markets. The time variations of stock returns display stylized fact tails and volatility clustering across all return series. This stressful period increased investor pessimism and fears and generated negative emotions. Interestingly, our findings point to a high spillover of shocks between the RavenPack sentiment index, the Islamic and conventional stock return indices and cryptocurrencies.

In addition, we found that the RavenPack COVID sentiment is the main net transmitter of shocks for all conventional market indices and those most Islamic indices and cryptocurrencies are net receivers. More interestingly, our results reveal that the daily levels of positive and negative shocks in stock market indices and cryptocurrencies induced by the COVID-19 pandemic affect these variables. They also show that fear and pessimism sentiment induced by the news related to coronavirus plays a major role in driving the values of cryptocurrencies more than other indices. We also found that Ethereum can serve as a hedge against pandemic-related news. In general, news related to the COVID-19 pandemic encourages people to invest in cryptocurrencies. These results support the view of previous studies suggesting that investor sentiment performance is affected by financial markets during the bubble period (e.g. Cheema *et al.*, 2020; Soltani and Boujelbene Abbes, 2022). Therefore, this can help fund managers adjust their portfolio risk exposure by including stocks that significantly respond to COVID-19 sentiment and those that do not. In fact, the

volatility mechanism and investor sentiment can be interesting for investors as it allows them to consider the dynamics of each market and thus optimize the asset portfolio allocation.

Notes

1. https://coinmarketcap.com/
2. RavenPack (https://coronavirus.ravenpack.com) provides media data related to COVID-19 issues.

References

Agosto, A. and Cafferata, A. (2020), "Financial bubbles: a study of co-explosivity in the cryptocurrency market", *Risks*, Vol. 8 No. 2, p. 34.

Akhtaruzzaman, M. and Shamsuddin, A. (2016), "International contagion through financial versus non-financial firms", *Economic Modelling*, Vol. 59, pp. 143-163.

Akhtaruzzaman, M., Boubaker, S. and Sensoy, A. (2021), "Financial contagion during COVID–19 crisis", *Finance Research Letters*, Vol. 38, 101604.

Al-Awadhi, A.M., Alsaifi, K., Al-Awadhi, A. and Alhammadi, S. (2020), "Death and contagious infectious diseases: impact of the COVID-19 virus on stock market returns", *Journal of Behavioral and Experimental Finance*, Vol. 27, 100326.

Alaoui Mdaghri, A., Raghibi, A., Thanh, C.N. and Oubdi, L. (2021), "Stock market liquidity, the great lockdown and the COVID-19 global pandemic nexus in MENA countries", *Review of Behavioral Finance*, Vol. 13 No. 1, pp. 51-68.

Ashraf, B.N. (2021), "Stock markets' reaction to Covid-19: moderating role of national culture", *Finance Research Letters*, Vol. 41, 101857.

Aslanidis, N., Bariviera, A.F. and Martínez-Ibañez, O. (2019), "An analysis of cryptocurrencies conditional cross correlations", *Finance Research Letters*, Vol. 31, pp. 130-137.

Banerjee, A.K., Akhtaruzzaman, M., Dionisio, A., Almeida, D. and Sensoy, A. (2022), "Nonlinear nexus between cryptocurrency returns and COVID–19 COVID-19 news sentiment", *Journal of Behavioral and Experimental Finance*, Vol. 36, 100747.

Bani-Khalaf, O. and Taspinar, N. (2022), "Oil and gold return spillover and stock market elasticity during COVID-19 pandemic: a comparative study between the stock markets of oil-exporting countries and oil-importing countries in the Middle East", *Resources Policy*, Vol. 79, 102935.

Baruník, J. and Křehlík, T. (2018), "Measuring the frequency dynamics of financial connectedness and systemic risk", *Journal of Financial Econometrics*, Vol. 16 No. 2, pp. 271-296.

Beneki, C., Koulis, A., Kyriazis, N.A. and Papadamou, S. (2019), "Investigating volatility transmission and hedging properties between Bitcoin and Ethereum", *Research in International Business and Finance*, Vol. 48, pp. 219-227.

Bianco, C. and Wildangel, R. (2020), "Infected: the impact of the coronavirus on the Middle East and North Africa", *Retrieved March*, Vol. 31, p. 2020.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D. and Hagfors, L.I. (2017), "On the hedge and safe haven properties of Bitcoin: is it really more than a diversifier?", *Finance Research Letters*, Vol. 20, pp. 192-198.

Bouri, E., Shahzad, S.J.H. and Roubaud, D. (2019), "Co-explosivity in the cryptocurrency market", *Finance Research Letters*, Vol. 29, pp. 178-183.

Bouri, E., Cepni, O., Gabauer, D. and Gupta, R. (2021), "Return connectedness across asset classes around the COVID-19 outbreak", *International Review of Financial Analysis*, Vol. 73, 101646.

Butler, K.C. and Domian, D.L. (1991), "Risk, diversification, and the investment horizon", *Journal of Portfolio Management*, Vol. 17 No. 3, p. 41.

Charfeddine, L., Benlagha, N. and Maouchi, Y. (2020), "Investigating the dynamic relationship between cryptocurrencies and conventional assets: implications for financial investors", *Economic Modelling*, Vol. 85, pp. 198-217.

Cheema, M.A., Man, Y. and Szulczyk, K.R. (2020), "Does investor sentiment predict the near term returns of the Chinese stock market?", *International Review of Finance*, Vol. 20 No. 1, pp. 225-233.

Corbet, S., Lucey, B. and Yarovaya, L. (2018), "Datestamping the Bitcoin and Ethereum bubbles", *Finance Research Letters*, Vol. 26, pp. 81-88.

Corbet, S., Larkin, C. and Lucey, B. (2020), "The contagion effects of the COVID-19 pandemic: evidence from gold and cryptocurrencies", *Finance Research Letters*, Vol. 35, 101554.

Dewandaru, G., Rizvi, S.A.R., Masih, R., Masih, M. and Alhabshi, S.O. (2014), "Stock market co-movements: islamic versus conventional equity indices with multi-timescales analysis", *Economic Systems*, Vol. 38 No. 4, pp. 553-571.

Diebold, F.X. and Yilmaz, K. (2012), "Better to give than to receive: predictive directional measurement of volatility spillovers", *International Journal of Forecasting*, Vol. 28 No. 1, pp. 57-66.

Diebold, F.X. and Yılmaz, K. (2014), "On the network topology of variance decompositions: measuring the connectedness of financial firms", *Journal of Econometrics*, Vol. 182 No. 1, pp. 119-134.

Fakhfekh, M. and Jeribi, A. (2020), "Volatility dynamics of crypto-currencies' returns: evidence from asymmetric and long memory GARCH models", *Research in International Business and Finance*, Vol. 51, 101075.

Feng, W., Wang, Y. and Zhang, Z. (2018), "Can cryptocurrencies be a safe haven: a tail risk perspective analysis", *Applied Economics*, Vol. 50 No. 44, pp. 4745-4762.

Forbes (2020), "Dow Jones futures drop: S&P 500 loses momentum, Covid-19 wave cracks stock market rally", available at: https://www.forbes.com/sites/naeemaslam/2020/06/25/dow-jones-and-sp500- futures-stocks-crash/#3583204450ee

Forbes, K.J. and Rigobon, R. (2002), "No contagion, only interdependence: measuring stock market comovements", *The Journal of Finance*, Vol. 57 No. 5, pp. 2223-2226.

Gil-Alana, L.A., Abakah, E.J.A. and Rojo, M.F.R. (2020), "Cryptocurrencies and stock market indices. Are they related?", *Research in International Business and Finance*, Vol. 51, 101063.

Goodell, J.W. and Goutte, S. (2021), "Co-movement of COVID-19 and Bitcoin: evidence from wavelet coherence analysis", *Finance Research Letters*, Vol. 38, 101625.

Gomes, O. and Gubareva, M. (2021), "Complex systems in economics and where to find them", *Journal of Systems Science and Complexity*, Vol. 34 No. 1, pp. 314-338.

Grinsted, A., Moore, J.C. and Jevrejeva, S. (2004), "Application of the cross wavelet transform and wavelet coherence to geophysical time series", *Nonlinear Processes in Geophysics*, Vol. 11 Nos 5/6, pp. 561-566.

Katsiampa, P., Corbet, S. and Lucey, B. (2019), "Volatility spillover effects in leading cryptocurrencies: a BEKK-MGARCH analysis", *Finance Research Letters*, Vol. 29, pp. 68-74.

Khaleej Times (2020), "Covid-19: GCC investors lose over Dh257 billion in a day as stock markets Plunge-1 March 2020", available at: https://www.khaleejtimes.com/business/markets/gulf-bourses-slip

KPMG (2020), "Potential impact of COVID-19 on the Qatar economy", available at: https://assets.kpmg/content/dam/kpmg/qa/pdf/2020/4/potential_impact_of_covid-19_on_the_qatar_economy_all%20sectors.pdf

Kristjanpoller, W. and Bouri, E. (2019), "Asymmetric multifractal cross-correlations between the main world currencies and the main cryptocurrencies", *Physica A: Statistical Mechanics and Its Applications*, Vol. 523, pp. 1057-1071.

Lahmiri, S. and Bekiros, S. (2019), "Cryptocurrency forecasting with deep learning chaotic neural networks", *Chaos, Solitons and Fractals*, Vol. 118, pp. 35-40.

Liu, W. (2019), "Portfolio diversification across cryptocurrenciesé", *Finance Research Letters*, Vol. 29, pp. 200-205.

Liu, Z., Huynh, T.L.D. and Dai, P.F. (2021), "The impact of COVID-19 on the stock market crash risk in China", *Research in International Business and Finance*, Vol. 57, 101419.

Mehdi, A., Gheraia, Z., Abdelli, H., Sekrafi, H. and Diaw, A. (2022), "COVID-19 pandemic and economic impacts in Arab countries: challenges and policies", *Research in Globalization*, 100103.

Mensi, W., Sensoy, A., Vo, X.V. and Kang, S.H. (2020), "Impact of COVID-19 outbreak on asymmetric multifractality of gold and oil prices", *Resources Policy*, Vol. 69, 101829.

Mink, M. (2015), "Measuring stock market contagion: local or common currency returns?", *Emerging Markets Review*, Vol. 22, pp. 18-24.

Mnif, E., Jarboui, A. and Mouakhar, K. (2020), "How the cryptocurrency market has performed during COVID 19? A multifractal analysis", *Finance Research Letters*, Vol. 36, 101647.

Narayan, P.K., Devpura, N. and Wang, H. (2020), "Japanese currency and stock market—what happened during the COVID-19 pandemic?", *Economic Analysis and Policy*, Vol. 68, pp. 191-198.

Ng, A. (2020), "Three ways the corona virus could have an impact on Middle East economies", *Retrieved March*, Vol. 12, p. 2020.

Omane-Adjepong, M. and Alagidede, I.P. (2019), "Multiresolution analysis and spillovers of major cryptocurrency markets", *Research in International Business and Finance*, Vol. 49, pp. 191-206.

Ozdamar, M., Sensoy, A. and Akdeniz, L. (2022), "Retail vs institutional investor attention in the cryptocurrency market", *Journal of International Financial Markets, Institutions and Money*, Vol. 81, 101674.

Pesaran, H.H. and Shin, Y. (1998), "Generalized impulse response analysis in linear multivariate models", *Economics Letters*, Vol. 58 No. 1, pp. 17-29.

Rua, A. and Nunes, L.C. (2009), "International comovement of stock market returns: a wavelet analysis", *Journal of Empirical Finance*, Vol. 16 No. 4, pp. 632-639.

Sayed, M.N. and Abbas, N.A. (2018), "Impact of crypto-currency on emerging market focus on gulf countries", *Life Science Journal*, Vol. 15 No. 1, pp. 92-97.

Sharif, A., Aloui, C. and Yarovaya, L. (2020), "COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach", *International Review of Financial Analysis*, Vol. 70, 101496.

Solomon, H. (2020), "The impact of covid-19 on the Middle East and North Africa", *Institute for Contemporary Affairs*, Vol. 20 No. 6.

Soltani, H. and Boujelbene Abbes, M. (2022), "The impact of the COVID-19 pandemic on the nexus between the investor's sentiment and the financial market dynamics: evidence from the Chinese market", *Asia-Pacific Journal of Business Administration*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/APJBA-07-2021-0326.

The World Bank Update (2020), "Oman's economic update – April 2020", available at: https://www.worldbank.org/en/country/gcc/publication/oman-economic-update-april-2020

Tiwari, A.K., Raheem, I.D. and Kang, S.H. (2019), "Time-varying dynamic conditional correlation between stock and cryptocurrency markets using the copula-ADCC-EGARCH model", *Physica A: Statistical Mechanics and Its Applications*, Vol. 535, 122295.

Yang, L., Cai, X.J., Zhang, H. and Hamori, S. (2016), "Interdependence of foreign exchange markets: a wavelet coherence analysis", *Economic Modelling*, Vol. 55, pp. 6-14.

Yi, S., Xu, Z. and Wang, G.J. (2018), "Volatility connectedness in the cryptocurrency market: is Bitcoin a dominant cryptocurrency?", *International Review of Financial Analysis*, Vol. 60, pp. 98-114.

Zhang, D., Hu, M. and Ji, Q. (2020), "Financial markets under the global pandemic of COVID-19", *Finance Research Letters*, Vol. 36, 101528.

Further reading

Böhme, R., Eckey, L., Moore, T., Narula, N., Ruffing, T. and Zohar, A. (2020), "Responsible vulnerability disclosure in cryptocurrencies", *Communications of the ACM*, Vol. 63 No. 10, pp. 62-71.

Q&A, F. A. O. (2020), *COVID-19 Pandemic-Impact on Food and Agriculture Q1: Will Covid-19 Have Negative Impacts on Global Food Security*, FAO, Rome.

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The interplay between firms' capabilities and ownership in explaining environmental performance

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Received 1 September 2022
Revised 5 April 2023
Accepted 16 April 2023

Abstract

Purpose – This study empirically assesses the effects of two key types of organizational and managerial capabilities—dynamic capabilities, and coordination and cohesion capabilities—on environmental performance, considering the moderating effect of family ownership. By applying the tenets of the natural resource-based view and the dynamic capabilities theory, this paper offers new insights into the topic.

Design/methodology/approach – The article presents empirical evidence from a survey of 1,019 firms operating in the Spanish tourism sector analyzed using multiple linear regression.

Findings – Overall, our results show that both dynamic capabilities and coordination and cohesion capabilities have direct and synergetic positive effects on environmental performance. In addition, the results confirm recent studies that report conflicting evidence on how family ownership affects environmental performance: family ownership is found to exert a distinct direct effect on environmental performance and on the development and application of the capabilities required to improve such performance.

Originality/value – This article sheds light on the conceptual frontiers between the different types of capabilities, as well as provides practical ways of measuring them. The article also brings evidence to bear on the debate concerning the direct and moderating effect that family ownership exerts on the relationship between both types of capabilities over environmental performance. The results of this analysis confirm the complexity of the family ownership effect on this aspect, and provide important insights for both business practitioners and academics.

Keywords Environmental performance, Dynamic capabilities, Coordination and cohesion capabilities, Family business, Tourism sector

Paper type Research paper

Funding: This research was funded by "Plan de promoción de la investigación de la UJI—Convocatoria 2021 de "Proyectos de investigación científica y desarrollo tecnológico" of the Universitat Jaume I (project ref. UJI-A2021-06) and from "Plan Estatal de Investigación Científica y Técnica y de Innovación 2021-2024" of the Ministerio de Ciencia e Innovación, with the reference PID2020-119642GB-I00. The author José María Fernández Yáñez has been supported by the predoctoral grant PD-UJI/2019/13.

European Journal of Management and Business Economics
Vol. 34 No. 1, 2025
pp. 47-66
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-09-2022-0272

1. Introduction

Environmental performance has taken centre stage in organizational strategy and politics as the impacts of modern consumerism and industrialization on the climate become clearer (United Nations, 2020; Leonidou *et al.*, 2015). A variety of actions fall within the scope of environmental performance; they include efforts to prevent environmental pollution, waste reduction, minimizing the consumption of materials, energy and water, enhancing the efficiency of equipment, maximizing the use of renewables, extending product life and ensuring that resources and products can be recycled (Forés, 2019; Amui *et al.*, 2017).

A growing number of studies show that firms improve their economic performance when they take into account ecological and interrelated social issues (e.g. Hang *et al.*, 2018), due to the strong relationships created with their stakeholders, cost containment, enhanced productivity, employee motivation and satisfaction, access to new markets, innovation, and a greater ability to take on environmental and societal challenges (Leonidou *et al.*, 2015).

Therefore, it is no longer a question of reacting to customers' demands or responding to legal requirements; rather, firms adopt an internal focus and strategy to integrate environmental concerns into their culture and management and operational principles, in order to ensure long-term economic viability and a sustained competitive advantage (Hart and Dowell, 2011; Hart, 1995).

In the sustainability and environmental performance literature, dynamic capabilities are attracting growing attention (Felsberger *et al.*, 2022; Duarte-Alonso *et al.*, 2020; Mousavi *et al.*, 2018; Amui *et al.*, 2017; Albort-Morant *et al.*, 2016). Given the highly dynamic and complex context in which firms deal with different emerging environmental issues (Forés, 2019; Aragón-Correa and Sharma, 2003), some recent studies suggest that a focus on dynamic capabilities can help us to better understand how firms change their organizational and managerial processes and routines to transition towards a sustainable industry (Eikelenboom and de Jong, 2019; Mousavi *et al.*, 2018).

To date, however, dynamic capability research has mainly sought to identify the effect of such capabilities on economic performance (Wu *et al.*, 2013). The literature has revealed how different processes that constitute dynamic capabilities – sensing, seizing and reconfiguring – (Teece, 2007) affect sustainability (Mousavi *et al.*, 2018). However, according to authors such as Eikelenboom and de Jong (2019), Mousavi *et al.* (2018) and Amui *et al.* (2017), there is still a need for more empirical research on how these dynamic capabilities, and their interaction with other managerial and organizational capabilities such as coordination and cohesion capabilities (Camisón and Villar-López, 2014; Camisón, 2005), impact environmental performance.

Coordination and cohesion capabilities comprise the managerial and organizational processes needed to activate, leverage and boost the efficiency and quality of the firm's existing resources and functional capabilities (Camisón and Villar-López, 2014; Camisón, 2005); they also represent a key source of advantage in terms of firms' environmental performance (Singh *et al.*, 2019; Fernández *et al.*, 2003), gradually adapting them to changes in the environment.

These capabilities include management skills related to the creation and communication of a strategic vision, and the development of a mission and culture that bolster cooperation, commitment, flexibility, an orientation towards quality and continuous improvement, and the transfer of knowledge (Camisón and Villar-López, 2014; Camisón, 2005; Lado *et al.*, 1992). Building this participatory, trust-based culture requires different organizational design mechanisms and procedures to define jobs, tasks and objectives, to organize teamwork, and to channel communication in all directions within the firm.

Environmental studies to date have primarily centred on manufacturing firms, with the tourism sector (and the service sector more generally) receiving far less attention (Reyes-Santiago *et al.*, 2019; Shang *et al.*, 2019). Nevertheless, tourism firms are heavily dependent on

water, energy and non-renewable resources, with potentially harmful effects on the environment and on competing tourism products (Sakshi *et al.*, 2019).

Family-owned firms dominate the tourism sector globally (Memili *et al.*, 2018), thus necessitating their analysis in this context. To that end, there is a need to consider the specific influence of family ownership structure and governance on both sustainability issues (e.g. Memili *et al.*, 2018) and dynamic capabilities (e.g. Chirico and Salvato, 2016), considering that the literature on these topics is generally scarce (Daspit *et al.*, 2019) but of particular importance for family firms.

Given that the sustainability and competitiveness of the tourism sector strongly depend on business owners' efforts to generate new development patterns, this study draws on the resource-based view (Barney, 1991) and its recent extensions the dynamic capabilities theory (DCT) (Teece *et al.*, 1997) and the natural resource-based view (NRBV) (Hart, 1995) to shed light on these crucial issues. To that end, the analysis involves developing and testing a model of the determinants of tourism firms' environmental performance relating to different types of managerial and organizational capabilities; namely, dynamic capabilities and coordination and cohesion capabilities.

This analysis adds to the literature on the topic as, to our knowledge, there is no study to date that empirically analyzes the effect of both types of capability on environmental performance. Moreover, this paper examines how family ownership may directly affect the achievement of environmental outcomes, or indirectly affect it through an influence on dynamic capabilities and coordination and cohesion capabilities. The analysis specifically addresses two main research questions:

RQ1. How do dynamic capabilities and coordination and cohesion capabilities impact and interact to determine environmental performance in the tourism business?

RQ2. How does family ownership directly influence environmental performance and moderate the relationship between the above capabilities and environmental performance?

Using cross-sectional data from 1,019 Spanish tourism firms, this study extends the literature on managing capabilities for environmental performance, making both theoretical and empirical contributions.

2. Hypotheses

2.1 Managerial and organizational capabilities and environmental performance

2.1.1 The direct effect of dynamic capabilities. Sensing capabilities are needed to identify environmental problems and the underlying environmental needs, and to gather information about the possible solutions accounting for customers' needs, suppliers' requirements, competitors' performance, the evolving regulatory framework and potential technological opportunities (Mousavi *et al.*, 2018).

The more varied the external sources from which the company identifies innovative and profitable answers to environmental problems, the greater the impact on environmental performance (Mousavi *et al.*, 2018; Dangelico *et al.*, 2017). For instance, green technology can depend on the cooperation between governments, specialized technological companies, energy suppliers and citizens.

Seizing involves the mobilization of resources and capabilities in order to apply the knowledge acquired to create valuable products/services, technologies and processes (Teece, 2007). Outsourcing and cooperation alliances with a variety of partners (Dangelico *et al.*, 2017), training programmes for product development and R&D staff (Dangelico *et al.*, 2017) and continuous experimentation with new clean technologies (Wu *et al.*, 2013) are examples of innovation processes that can put sensed knowledge into use.

Reconfiguring processes enables the renewal of resources and capabilities by combining them in different ways to meet the environmental requirements of the changing competitive arena (Mousavi *et al.*, 2018). Reconfiguration processes also allow firms to reinvent or modify the technology according to their needs.

According to Dangelico *et al.* (2017), reconfiguring could involve creating a new green division, integrating environmental specialists and radically changing the relationships along the supply chain. Wu *et al.* (2013) also point to the importance of boosting this capacity by performing audits and risk analysis focused on the potential factors that cause environmental impacts, and by introducing standard environmental management systems such as ISO 9000 and ISO 14001.

Although most studies analyzing the effect of dynamic capabilities on environmental performance are theoretical reviews (e.g. Amui *et al.*, 2017), exploratory studies or qualitative analyses (e.g. Wu *et al.*, 2013), there has been a growing number of empirical studies on the topic in the last five years. However, to the best of our knowledge, there are no such studies to date focusing on the tourism sector.

Albort-Morant *et al.* (2016) empirically demonstrate that dynamic capabilities can shape sustainable innovation performance by reconfiguring the learning that occurs between the organization and its customers.

Dangelico *et al.* (2017) find that external and internal resource integration and reconfiguration allows firms to develop new or significantly improved green products and processes, minimizing manufacturing emissions or energy and increasing the recyclability and remanufacturability of products.

Mousavi *et al.* (2018) demonstrate that sensing, seizing and reconfiguring capabilities have an important effect on innovation, helping to improve sustainability. These results are particularly notable for sensing activities.

Finally, Eikelenboom and de Jong (2019) empirically show that "external integrative dynamic capabilities", related to processes that integrate the resources and capabilities of parties outside the organizations such as suppliers and customers, are positively related to environmental performance.

In light of the above arguments, we posit the following hypothesis:

H1. There is a positive relationship between a firm's dynamic capabilities and its environmental performance.

2.1.2 The direct effect of coordination and cohesion capabilities. Good environmental performance may be achieved by creating new resources and capabilities, applying dynamic capabilities (hypothesis 1), and/or extending or modifying existing ones in more efficient ways.

Coordination and cohesion capabilities could introduce organizational changes and modifications of the firm's resources and capabilities in ways that could impact environmental performance: for example, in the acquisition of knowledge, the design and launch of a product or service, and the improvement of equipment and process efficiency.

Top management support can influence environmental performance by promoting employee empowerment to drive cultural changes, implementing systems to encourage desired behaviours through rewards or incentives, providing training, and stimulating cooperation and coordination throughout the organization (Roscoe *et al.*, 2019; Fernández *et al.*, 2003).

When employees are empowered to make their own decisions, they are given the autonomy to identify and quickly rectify damaging activities in a firm's operations (Leonidou *et al.*, 2015; Fernández *et al.*, 2003). In addition, employees can be given the opportunity to carry out audits of their own processes and those of their colleagues to encourage a culture of continuous environmental improvement (Roscoe *et al.*, 2019).

Although commitment from top management is essential, its efficacy depends on the constant flow of information between management and employees (Fernández *et al.*, 2003).

Through teamwork and cross-functional mechanisms, an organization can also develop a shared collective vision and commitment to environmental matters (Leonidou *et al.*, 2015).

Moreover, once a firm is committed to achieving environmental aims, it should also provide the appropriate resources to support training that reinforces employees' concerns about and emotional involvement in environmental issues (Fernández *et al.*, 2003). Ideally, such training would involve interactive skills, benchmarking, team building and consensus-building (Fernández *et al.*, 2003). These skills are crucial to implementing this environmental knowledge and creative solutions.

Specifically focusing on the hospitality and tourism sector, Chan *et al.* (2018) claim that employees' environmental attitudes are key to successful green technology implementation in hotels. Sakshi *et al.* (2019) also demonstrate that environmental policy and training enhances communication on environmental issues and promotes recycling and resource and energy conservation, with a clear impact on environmental performance.

Therefore, we hypothesize the following:

H2. There is a positive relationship between a firm's coordination and cohesion capabilities and its environmental performance.

2.1.3 The moderating effect of coordination and cohesion capabilities on the relationship between dynamic capabilities and environmental performance. The literature underlines the value of coordination and cohesion capabilities for the effective and efficient application of dynamic capabilities to improve environmental performance (Shang *et al.*, 2019). These coordination and cohesion capabilities can provide firms with flexible organizational structures that allow them to apply the innovation processes underlying dynamic capabilities to environmental purposes (Roscoe *et al.*, 2019; Shang *et al.*, 2019).

In order to innovate in environmental issues, it is essential for firms to avoid conventional thinking and clichéd practices (Eikelenboom and de Jong, 2019). Top-level management can play a key role in this regard: indeed, authors such as Eikelenboom and de Jong (2019) report that if managers feel a need to adjust their business to environmental requirements, they will foster the development of dynamic capabilities.

By increasing the frequency and quality of the interactions with external actors, coordination and cohesion capabilities could support the sensing capabilities linked to scanning, searching and exploring markets and technologies for opportunities related to environmental performance (Mousavi *et al.*, 2018; Leonidou *et al.*, 2015).

The seizing of new environmental knowledge and practices entails a major shift in technology, equipment and procedures, which could not be implemented without support from the firm's employees (Leonidou *et al.*, 2015). In this vein, coordination and cohesion capabilities enhance the seizing processes involved in the exploitation of new knowledge, lending legitimacy to environmental performance improvement. Within this seizing process, cooperation also facilitates the sharing of problem-solving expertise, which can reduce the risks and investment involved in producing environmental outputs (Mousavi *et al.*, 2018).

Coordination and cohesion capabilities can also reinforce the reconfiguring capabilities needed to adapt existing processes and resources, through cross-functional teams, steering committees and employee training (Mousavi *et al.*, 2018) for environmental purposes.

Therefore, we posit the following hypothesis:

H3. Coordination and cohesion capabilities exert a positive moderating effect on the relationship between dynamic capabilities and environmental performance.

2.2 Family ownership and environmental performance

2.2.1 The direct effect of family ownership. The family business literature has recently been focusing more attention on environmental performance (Dangelico *et al.*, 2019; Berrone *et al.*, 2010),

due to the important role it plays in the success of the business and the survival of the economic system (Samara *et al.*, 2018). According to recent literature, family businesses are more likely to implement sustainability practices that go beyond regulations and external pressure (Le Breton-Miller and Miller, 2016; Berrone *et al.*, 2012; Sharma and Sharma, 2011). Family businesses show an increased awareness of environmental responsibility as they seek to preserve their Socioemotional Wealth (SEW) (Samara *et al.*, 2018; Gómez-Mejía *et al.*, 2007).

Since environmental performance is key to the long-term prosperity of a business, family businesses may pursue the design of products and services that demonstrate environmental awareness and help to build customer loyalty by developing an image of quality associated with the family name (Memili *et al.*, 2018) and family-based values of trust, care and support (Bammens and Hünermund, 2020). In addition, family businesses are more likely to be motivated by long-term financial benefits (Dangelico *et al.*, 2019), providing patient capital for environmental performance. They are also more likely to feel burdened by institutional pressures such as environmentally friendly policies (Le Breton-Miller and Miller, 2016).

Some empirical studies demonstrate that family businesses tend to show better environmental performance (e.g. Bammens and Hünermund, 2020; Gómez-Mejía *et al.*, 2019; Berrone *et al.*, 2010) with less volatility than other firms. They are also more likely to adopt proactive environmental strategies (e.g. Sharma and Sharma, 2011), obtain environmental certifications and publish a variety of reports about their environmental activities (e.g. Campopiano and De Massis, 2015).

Specifically, family businesses in the tourism sector show greater environmental awareness due to their strong dependence on their surrounding natural environment, and high degree of embeddedness in the local community (Bammens and Hünermund, 2020; Dekker and Hasso, 2014; Berrone *et al.*, 2010).

However, as pointed out above, there is still relatively little literature examining the relationship between family business ownership and environmental performance, and the findings are contradictory (Graafland, 2020). In this respect, studies such as that by Cruz *et al.* (2014) do not report a significant relationship between the two constructs. Graafland (2020) finds that the relationship between family ownership and environmental performance is stronger in smaller companies that also have a combination of family and non-family members in managerial positions.

Other researchers such as Le Breton-Miller and Miller (2016) argue that family members' desire for control over the firm may trigger conservatism instead of efforts to revitalize the firm. This claim is in line with empirical research showing that family businesses underperform their non-family counterparts in environmental performance (Dal Maso *et al.*, 2020).

Despite this contradictory evidence in the emerging literature, we hypothesize the following:

H4. There is a positive relationship between family ownership and environmental performance.

2.2.2 The moderating effect of family ownership on the relationship between dynamic capabilities and environmental performance. The above-mentioned controversy about the effect of family ownership on sustainability performance also extends to the study of the impact of family ownership on one of the main antecedents of such performance: dynamic capabilities. Despite the growing interest in the study of dynamic capabilities in family businesses (e.g. Chirico and Salvato, 2016) due to their key role in ensuring ongoing adaptation to a shifting environment and long-term competitiveness (Barros *et al.*, 2016), the results are not conclusive.

Some studies point to family businesses as being particularly innovative, dynamic and proactive (e.g. Chirico and Salvato, 2016). Viewed from this perspective, family dynamics enhance the generation and sharing of specific tacit knowledge (Barros *et al.*, 2016; Chirico and Salvato, 2016), among family members and non-family stakeholders such as suppliers or community members, allowing superior orchestration of resources and capabilities to improve environmental performance (Shang *et al.*, 2019).

Conversely, other scholars suggest that the desire to protect family wealth for future generations and the emotional attachment to family-endowed resources lead to risk-aversion (e.g. König *et al.*, 2013; Naldi *et al.*, 2007) and the avoidance of strategic change (e.g. Carnes and Ireland, 2013).

Even when family owners have the power, legitimacy and authority to develop and apply dynamic capabilities, they might hesitate to enforce these new capabilities if they require capital investment, external resources and dependence on external professionals, and if they may adversely affect SEW by reducing family control (Memili *et al.*, 2018).

In addition, highly committed family leaders might view their firms as personal fiefdoms, and thus be unwilling to accept novel thinking and new combinations of resources that deviate from previous paths and strategies (König *et al.*, 2013), perceiving them to be a violation of family traditions and culture. Emotional ties to existing assets and organizational structures can also reduce family businesses' creativity and willingness to rapidly adopt new technology and processes needed for dynamic capabilities (König *et al.*, 2013), limiting their scope and application to environmental aims.

The above arguments lead to the following hypothesis:

H5. Family ownership exerts a negative moderating effect on the relationship between dynamic capabilities and environmental performance.

2.2.3 The moderating effect of family ownership on the relationship between coordination and cohesion capabilities and environmental performance. Similarly, the review of the family business literature does not yield conclusive results on the effect that family ownership can have on coordination and cohesion capabilities and their application to environmental concerns. The family business is characterized by a structure based on the close interaction of kinship ties and reciprocal trust between family members (Berrone *et al.*, 2012). The alignment between ownership and management in family firms fosters organizational flexibility (e.g. Dangelico *et al.*, 2019), top management (e.g. Dangelico *et al.*, 2019) and employee commitment to continuously share and incorporate specialized knowledge to promote action (e.g. Daspit *et al.*, 2019).

These family business characteristics and alignment of goals and resources can thus enhance the quality and efficiency of internal knowledge exchange, existing processes and technologies, which in turn can be directed at improving environmental performance (Samara *et al.*, 2018; Le Breton-Miller and Miller, 2016; Berrone *et al.*, 2012). Previous studies show that family businesses behave much more responsibly than their non-family counterparts and continuously seek new ways to manage and organize their resources and capabilities in a manner that protects and preserves the natural environment in which the firm is embedded (Sharma and Sharma, 2011; Berrone *et al.*, 2010).

However, family involvement in ownership and management can also be associated with less desirable behaviours such as nepotism and the entrenchment of family members (Carnes and Ireland, 2013). Such behaviour may lead family members to act opportunistically to secure private benefits and generate intra-family conflicts, which can restrict the ability of family businesses to pursue environmental aims (Samara *et al.*, 2018; Le Breton Miller and Miller, 2016). Ultimately, these situations can lead to suboptimal use of the organization's resources and to family members neglecting their responsibilities to improve the

environmental sustainability of the community in which the company is embedded (Le Breton-Miller and Miller, 2016).

Despite these conflicting arguments, we expect family ownership to enhance the effect of coordination and cohesion capabilities on environmental performance. Thus, we hypothesize the following:

H6. Family ownership exerts a positive moderating effect on the relationship between coordination and cohesion capabilities and environmental performance.

The conceptual model shown in Figure 1 summarizes the above hypotheses.

3. Methodology

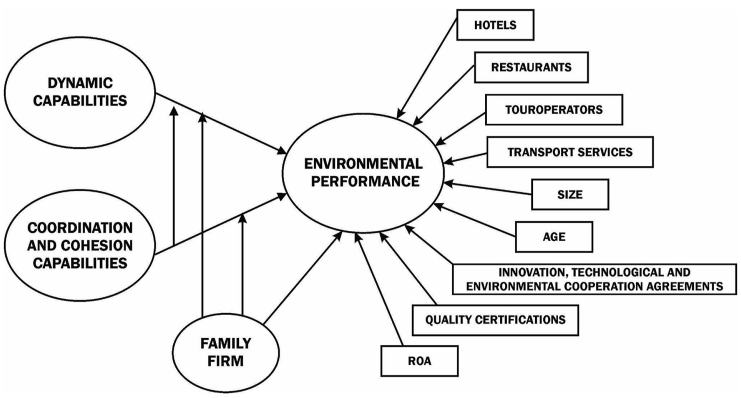
3.1 Data

The database for this study consists of 1,019 firms, of which 748 are family businesses and 271 non-family businesses, operating in the Spanish tourism sector; relative to the total population, this represents a margin of error of ±3.1% (confidence interval 95.5%). Data used to create the database were obtained using a questionnaire administered to the firm's owner, CEO or general manager. A modified version of Dillman's Total Design Method (Dillman, 1978) was applied in order to deal with issues commonly associated with surveys and questionnaires as a means of collecting data. Before employing the final questionnaire, it was pretested on five specialist scholars in the fields of tourism and strategy.

The data collected from the questionnaire were then completed with information from SABI (Iberian Balance Sheet Analysis System) database. The fieldwork was conducted from December 2009 to March 2010.

3.2 Variables

Environmental performance, coordination and cohesion capabilities and dynamic capabilities were measured using 7-point multi-item scales, reflecting managers' perception of their firm's performance and its endowment of capabilities. In each question, respondents had to compare their firm's position and strength to that of competitors in their specific subsector (from 1 = "much worse" to 7 = "much better"). The measurement of these variables has been shown to be consistent and reliable, with Cronbach's Alpha well above the 0.7 threshold proposed by Hair *et al.* (1998).



Source(s): own elaboration

Figure 1.
Conceptual framework

These three variables were introduced into the model as the arithmetic mean of the items included in their respective measurement scales. This procedure has long been used in strategic research, and offers advantages over other methods (such as using factor scores after summarizing the information through an exploratory factor analysis of the items of each scale) because it maintains the comprehensive definition of the domain of the constructs.

3.2.1 Dependent variable. 3.2.1.1 Environmental performance (ENVPERF). This variable comprises five items adapte from previous studies (e.g. Zhu and Sarkis, 2007) also validated in recent literature (e.g. Forés, 2019) (Appendix A).

3.2.2 Independent variables. 3.2.2.1 Family ownership of the business (FB). To evaluate the family ownership of the business, we used the following question: "Is this a family business?" This question is the basis of the dummy variable FB, which takes a value of 1 if the firm self-identifies as a family business. Recent studies such as that by Dekker and Hasso (2014) also employ this self-reported family firm classification.

3.2.2.2 Dynamic capabilities (DYNCAP). The construct was formulated to include the three aspects identified by Teece (2007), which were similarly applied in later literature on this issue (Fitz-Koch and Nordqvist, 2017) (Appendix A).

3.2.2.3 Coordination and cohesion capabilities (COORCAP). The measurement of this variable was based on a 12-point scale adapted from Camisón and Villar-López (2014) and Camisón (2005), and also validated in recent empirical studies (e.g. Medase and Abdul, 2021; Chraratsari *et al*., 2018; González-Cruz *et al*., 2018). The measurement of the variable included items to capture the cooperation and teamwork inside the firm; the flexibility of approaches employed to organize the work; employees' commitment to the firm's values, mission and goals; and managerial support for employees' initiatives (Appendix A).

3.2.3 Control variables. We also included a number of control variables based on previous related studies by Berrone *et al.* (2010) and Dekker and Hasso (2014), which could have an effect on environmental performance.

As profitable firms may be better able to concentrate on environmental issues, we decided to control this factor (Hang *et al*., 2018; Dekker and Hasso, 2014; Berrone *et al*., 2010). We operationalized this item using the mean of the **Return on Assets** (ROA) estimated with information from the SABI database. It is measured as the average annual ROA over the period 2014–2010.

Size (SIZE) affects the ability of a firm to achieve economies of scale related to innovation. As such, it is often considered a predictor of environmental performance (e.g. Berrone *et al*., 2010). We measured size as the total number of employees.

Age (AGE) can influence a firm's proactive environmental management and public visibility (Wang *et al*., 2015) by drawing on the accumulated experience. We measured it as the number of years since the first establishment was opened.

Four dummy variables were included to capture the various **subsectors of tourist firms** in the sample, which presumably display different patterns of environmental performance. They are accommodation firms (HOTEL), restaurants (RESTA), travel agencies and tour operators (TOUR), and transport organizations (TRANSP), with complementary firms as the reference subsector.

We also controlled the number of **quality management certifications (QMC)**, considering the sum of the total number of ISO 14001, EMAS and other environmental norms, due to their important impact on environmental initiatives (Forés, 2019).

Finally, we introduced the **number of cooperation agreements (COOP)** established on innovation, and technological and environmental management issues, due to their reported effect on emissions reduction and pollution prevention (Albino *et al*., 2012).

Table 1 shows the descriptive statistics and correlations among the study variables. There is a low level of correlation (below 0.6) between the variables (see Table 1) (Podsakoff *et al*., 2003), which confirms the discriminant validity of the model.

Table 1.
Descriptive statistics and correlations of the study variables

VARIABLES	μ	σ^2	1	2	3	4	5	6	7	8	9	10	11	12	13
1. ENVPERF	3.618	1.386	1.000												
2. HOTEL	0.300	0.458	0.108***	1.000											
3. RESTA	0.378	0.485	−0.119***	−0.512***	1.000										
4. TOUR	0.109	0.312	0.097***	−0.230***	−0.274***	1.000									
5. TRANSP	0.039	0.194	0.074***	−0.132***	−0.158***	−0.071**	1.000								
6. SIZE	42.091	237.733	0.113***	0.147***	−0.101***	0.008	0.005	1.000							
7. AGE	18.551	19.880	0.082***	0.145***	−0.042*	−0.066**	0.003	0.022	1.000						
8. QMC	0.183	0.411	0.196***	0.207***	−0.116***	−0.086***	0.042*	0.176***	0.104***	1.000					
9. COOP	0.229	0.578	0.139***	0.149***	−0.149***	0.076***	−0.044*	0.205***	0.025	0.174***	1.000				
10. ROA	3.894	1.021	0.130***	0.067**	−0.062**	0.037	0.024	0.044*	−0.011	0.054**	0.101***	1.000			
11. DYNCAP	3.721	1.254	0.412***	0.105***	−0.168***	0.139***	−0.003	0.101***	−0.042*	0.210***	0.242***	0.193***	1.000		
12. COORCAP	3.552	1.367	0.213***	0.044*	−0.085***	0.049*	0.097***	0.099***	0.080***	0.217***	0.222***	0.233***	0.221***	1.000	
13. FB	0.734	0.442	0.062**	0.021	0.095***	−0.065**	0.042*	−0.094***	0.073**	−0.043*	−0.047*	−0.068***	−0.49*	−0.171***	1.000

Note(s): *** Correlation significant at the 0.01 level (bilateral)
** Correlation significant at the 0.05 level (bilateral)
* Correlation significant at the 0.1 level (bilateral)
Source(s): Own elaboration

3.3 Method of analysis

To test the research hypotheses, we ran a hierarchical regression analysis using SPSS 25.0. Before incorporating the moderating effects, the main variables were mean-centred to reduce multicollinearity (Cohen *et al.*, 2003; Aiken *et al.*, 1991). The variance inflation factors (VIF) confirmed that multicollinearity is not a problem: the highest VIF is 2.050, i.e. far below the threshold of 10 (Cohen *et al.*, 2003) (Appendix B contains the tests for residual analysis, homoscedasticity and sample normality).

4. Results

Table 2 displays the results of the model for each of the relationships under analysis. As can be seen, the F-test of significance is acceptable for all the models estimated. For the complete model including both direct and moderating effects, the value of R^2 indicates that it explains 23.4% of the variance in environmental performance.

Model 1 illustrates the relationship between control variables and environmental performance. The analysis of the control variables reveals that economic profitability, size and age all have small but positive significant effects on environmental performance (0.1, $p < 0.05$; 0.051, $p < 0.1$; 0.060, $p < 0.1$, respectively). Quality management certifications and cooperation agreements also report positive and significant coefficients (0.153, $p < 0.01$; 0.073, $p < 0.05$, respectively). Regarding the subsector variables, only hotels (0.106, $p < 0.05$), tour operators (0.145, $p < 0.01$) and transport (0.097, $p < 0.01$) report positive and significant effects on environmental performance, compared to the complementary offer subsector.

		Model I		Model II		Model III	
		(1)	(2)	(1)	(2)	(1)	(2)
	Constant	10.988**(3)	2.594	12.672***(3)	3.204	12.703***(3)	3.226
1	Hotel	0.106**	2.480	0.081**	2.030	0.086**	2.170
2	Resta	0.032	0.764	0.038	0.957	0.040	1.023
3	Tour	0.145***	3.978	0.094***	2.768	0.093***	2.738
4	Transp	0.097***	2.976	0.079***	2.600	0.082***	2.708
5	Size	0.051*	1.652	0.051*	1.773	0.044	1.510
6	Age	0.060*	1.957	0.068**	2.394	0.069**	2.426
7	QMC	0.153***	4.853	0.078***	2.609	0.073**	2.441
8	Coop	0.073**	2.320	−0.004	−0.132	−0.003	−0.115
9	ROA	0.100***	3.308	0.030	1.032	0.034	1.171
5	Dyncap			0.356***	11.775	0.347***	11.418
6	Coorcap			0.105***	3.433	0.098***	3.183
7	FB			0.100***	3.490	0.101***	3.473
10	Dyncap × FB					−0.070**	−2.398
11	Coorcap × FB					0.001	0.049
12	Dyncap × Coorcap					0.059**	2.024
	F	11.451***		24.261***		20.391***	
	R^2	0.093		0.224		0.234	
	Adjusted R^2	0.085		0.215		0.222	
	Changes in R^2	–		0.132		0.009	

Note(s): (1) Standardized regression coefficients
(2) *t*-values
(3) Non-standardized beta
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$
Source(s): Own elaboration

Table 2.
Estimation results

Model 2 incorporates the direct effects of the explanatory variables on dynamic capabilities, coordination and cohesion capabilities and family ownership. The empirical results show that both dynamic capabilities and coordination and cohesion capabilities have positive significant effects on environmental performance (0.356, $p < 0.01$; 0.105, $p < 0.01$, respectively), supporting our first two hypotheses.

Model 2 also includes the direct effect that family ownership exerts on environmental performance. The empirical results confirm the positive and significant effect of family ownership on environmental performance (0.100, $p < 0.01$). Therefore, hypothesis 4 is also empirically supported.

The results from Model 3 allow us to explore the interaction terms. Although it is a small effect, empirical results confirm the positive and significant moderating effect exerted by coordination and cohesion capabilities on the relationship between dynamic capabilities and environmental performance (0.059, $p < 0.05$).

Results also show that family ownership exerts a negative and significant moderating effect on the relationship between dynamic capabilities and environmental performance (−0.070, $p < 0.05$), as predicted in hypothesis 5. Conversely, it has a non-significant positive moderating effect on the relationship between coordination and cohesion capabilities and environmental performance (0.001; $p > 0.1$). Therefore, we cannot accept hypothesis 6.

However, the model does not make it clear how the significant moderating effects exert their influence on environmental performance. In this respect, Aiken *et al.* (1991) suggest graphing the main effects given the conditional effect under study.

As shown in Figure 2, the positive moderating effect of coordination and cohesion capabilities on the relationship between dynamic capabilities and environmental performance is significant even for very low levels of dynamic capabilities (a threshold of 2, equivalent to a dynamic capabilities endowment of 28%), thus supporting hypothesis 3.

Figure 3 depicts the family ownership effect on the relationship between dynamic capabilities and environmental performance. The figure shows that family-owned firms achieve lower levels of efficiency in the application of dynamic capabilities to enhance environmental performance compared to their non-family counterparts, up to a relatively

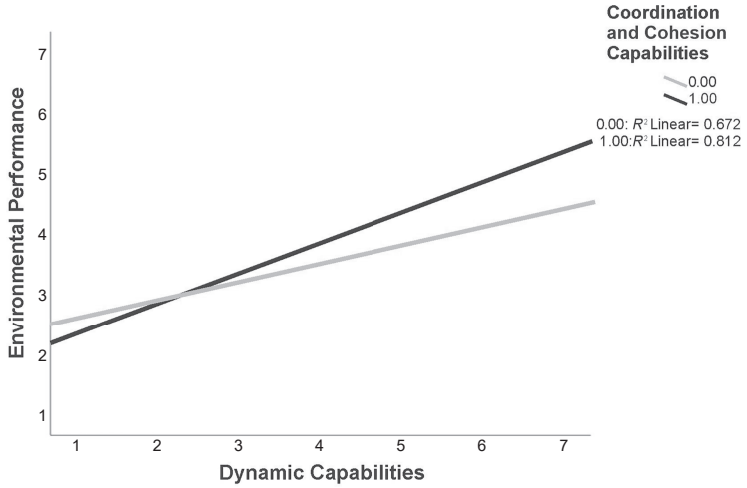
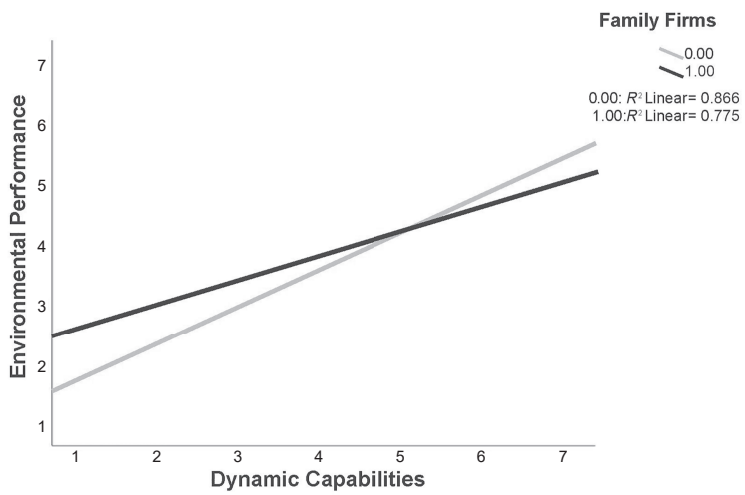


Figure 2.
Moderating effect of coordination and cohesion capabilities on the relationship between dynamic capabilities and environmental performance

Source(s): Own elaboration



Source(s): Own elaboration

Figure 3.
Moderating effect of family ownership on the relationship between dynamic capabilities and environmental performance

high level of dynamic capabilities endowment (a threshold of 5, equivalent to a dynamic capabilities endowment of 71%). Below this threshold, it can be seen that the effect of dynamic capabilities on environmental performance is higher for family-owned firms compared to their non-family counterparts. These findings partially support our hypothesis 5 and deserve further examination.

4.1 Robustness test

In addition to the common tests for the quality of fit and performance, which support the acceptability of our estimates, we performed a robustness check of our moderated model. Specifically, we conducted a moderation analysis using the PROCESS macro 2 that Hayes (2017) introduced in the SPSS software. The tool uses a conditional process analysis to examine the relationship between dynamic capabilities and environmental performance under the moderation of two variables: coordination and cohesion capabilities and family ownership. As the moderating effect between coordination and cohesion capabilities and family ownership is not significant (see Table 2) and the PROCESS macro does not offer a specific model to test the three moderating effects, we take model 2 as the most appropriate one.

When conducting this analysis, we take into account the Lower Limit Confidence Interval (LLCI) and the Upper Limit Confidence Interval (ULCI). For the interaction between dynamic capabilities and coordination and cohesion capabilities, we obtain an LLCI value of 0.007 and ULCI of 0.104; therefore, both are different to 0, and the output is based on a p-value ($p < 0.05$) to indicate a significant moderating effect, as described in hypothesis 3 and also shown in the hierarchical regression (Table 2).

We also confirm the moderating effect that family ownership exerts on the relationship between dynamic capabilities and environmental performance, with an LLCI value of −0.359 and ULCI of −0.061, ($p < 0.05$), confirming the results obtained for hypothesis 5 (see also Table 2).

For this model, the value of overall R^2 indicates that it explains 25.81% of the variance in environmental performance. Table 3 confirms that both coordination and cohesion capabilities

Table 3.
Results of moderation analysis using PROCESS macro (Model 2 with two interactions)

Model summary						
R	*R*-sq	MSE	F	df1	df2	p
0.508	0.258	1.565	520.321	5	748	0.000

Model	coeff	se	t	p	LLCI	ULCI
constant	3.418	0.088	38.706	0.000	3.245	3.591
DYNCAP	0.629	0.065	9.627	0.000	0.501	0.757
COORCAP	0.100	0.036	2.762	0.006	0.029	0.172
FB						
DYNCAPXCOORCAP	0.056	0.025	2.259	0.024	0.007	0.104
DYNCAPXFB	−0.210	0.076	−2.761	0.006	−0.359	−0.061

Source(s): Own elaboration

and family ownership are significant moderators (beta = 0.056, $p < 0.05$; beta = −0.21, $p < 0.05$, respectively) of the effect of dynamic capabilities on environmental performance.

5. Discussion

Firms are being called on to be both increasingly competitive and more environmentally responsible. In this context, the ability to generate competitive advantages associated with environmental performance is paramount for firms' survival (Wang *et al.*, 2015), particularly tourism firms (Chan *et al.*, 2018).

Drawing on the NRBV (Hart and Dowell, 2011; Hart, 1995) and the DCT (Teece, 2007; Teece *et al.*, 1997), this study contributes to the discussion on the topic. It presents an empirical analysis of two key managerial and organizational capabilities – dynamic capabilities and coordination and cohesion capabilities – and ownership structure, linked to family involvement in the business.

Previous research has illustrated the role of dynamic capabilities in innovation aimed at achieving environmental outcomes both in manufacturing (e.g. Felsberger *et al.*, 2022; Eikelenboom and de Jong, 2019; Mousavi *et al.*, 2018) and, recently, in the tourism sector (e.g. Duarte-Alonso *et al.*, 2020; Reyes-Santiago *et al.*, 2019; Leonidou *et al.*, 2015), which is the focus of analysis of this research.

However, these studies do not reveal the interactions with other important managerial and organizational capabilities, such as coordination and cohesion ones, in the development of new, more environmentally friendly processes and products. Furthermore, they do not take into consideration the effect of family ownership. Family-owned firms dominate the tourism sector globally (Memili *et al.*, 2018), making it essential to study the effect of family ownership on these issues.

The results of this study confirm that both dynamic capabilities and coordination and cohesion capabilities have a direct positive impact on environmental performance. The results also show that coordination and cohesion capabilities have a moderating effect on the capacity of dynamic capabilities to improve environmental performance. In this vein, managers should be aware that the deployment of dynamic capabilities is a continuous process.

Moreover, the results of this analysis show that family ownership has a complex effect on environmental performance. This supports recent theoretical and empirical research pointing to the ambivalence of the findings regarding the influence of family ownership on environmental performance (e.g. Graafland, 2020; Cruz *et al.*, 2014).

On the one hand, the results show that family ownership exerts a significant and positive direct effect on environmental performance, a result that lends support to the tenets of SEW theory, suggesting that continuity concerns can help family firms improve environmental performance (e.g. Bammens and Hünermund, 2020; Gómez-Mejía *et al.*, 2019; Berrone *et al.*, 2010).

However, this effect may be confounded by the impact that dynamic capabilities appear to have on environmental performance. In this regard, the results obtained support previous studies which find that family ownership may suppress the improvement of environmental performance if it requires innovation capabilities and a degree of risk (e.g. Carnes and Ireland, 2013). That said, this negative moderating effect only seems to hold for high levels of dynamic capabilities.

The state of the research thus suggests that the relationship between family ownership and innovation is more complex than initially supposed. Chrisman and Patel (2012) show that perceived threat to SEW is linked to higher marginal increases in R&D investments in family businesses than in other firms. Authors such as Diéguez-Soto *et al.* (2016) also point out that family managers may become risk tolerant and react strongly when the long-term consequences of technological innovation outcomes for firm performance are not adequate, thus becoming more effective at leveraging the family firm's unique resources.

Therefore, our results support previous studies framed in the behavioural theory logic, suggesting that conservative, risk-averse attitudes in family businesses (e.g. König *et al.*, 2013) might be reversed when the business and, more specifically, family SEW is under significant threat (Memili *et al.*, 2018; Chrisman and Patel, 2012; Gómez-Mejía *et al.*, 2007).

In this vein, we suggest that in firms with a low or medium endowment of dynamic capabilities, where the family's socioemotional capital (Barros *et al.*, 2016) and long-run sustainability of the family business are under threat (Berrone *et al.*, 2012), decision-makers may favour strategies that balance continuity and innovation aimed at the protection of the environment and ensuring the welfare of the local community (Berrone *et al.*, 2010).

In these situations, managers can forgo short-term gains and develop patient capital and long-term investments that support environmental innovation, as good environmental performance may boost the firm's image and reputation, that is the quest for legitimacy in the eyes of stakeholders to operate, and support the family's affective needs (Dekker and Hasso, 2014).

However, the opposite may occur when the family business has a large endowment of dynamic capabilities, as indicated by our results. In this scenario, firms might perceive that they maintain their competitive position in the market thanks to their innovation advantages and differentiation, and pursue the achievement of objectives that go beyond non-economic, environmental goals. Family businesses with a high level of dynamic capabilities may focus more on securing economic benefits from those capabilities, being driven by the logic of capitalism or the market, rather than using them to protect their SEW and improve environmental performance.

The non-significant moderating effect of family ownership on the relationship between coordination and cohesion capabilities and environmental performance confirms the inconclusive results of previous research. This finding suggests that family businesses should develop some strategies and invest in governance mechanisms supporting the professionalization process of the management team and the family members.

As for the control variables, this study confirms previous results reported by Dekker and Hasso (2014) and Berrone *et al.* (2010) showing that economic profitability, size and age have a positive effect on environmental performance, as expected. The results also show the

significant positive effect of quality certifications and cooperation agreements on environmental performance, confirming previous studies by Forés (2019) and Albino *et al.* (2012), respectively. Lastly, according to the results of this study, the most environmentally conscious companies are found to be tour operators and travel agencies, hotels and transport companies.

5.1 Managerial and public implications

In order to compete in the tourism sector, managers have to formulate strategies to renew, adapt, improve and even discard their resource base by means of dynamic capabilities that incorporate new knowledge and capacities into the firm (Teece, 2007). Moreover, these strategies should seek to mitigate the negative impact of their products, services and operations on the natural environment (Hart and Dowell, 2011; Hart, 1995). The need to promote the generation of dynamic capabilities is even greater for the tourism sector, especially since the survival of its business model involves extreme safety measures to prevent the spread of the COVID-19 pandemic.

Family owners should thus bear in mind that although innovation pays off in the market, their environmental performance is also an essential value in this new competitive arena, and one which supports their *raison d'être*: intergenerational succession.

Given the synergies that emerge between dynamic capabilities and coordination and cohesion capabilities, managers should promote two-pronged strategies when it comes to investing in the development of capabilities to achieve maximum efficiency and effectiveness in the firm's response to environmental challenges.

Managers of family firms should be especially concerned with the importance of training to empower employees to participate in environmental improvement and protection. Family firms should also invest in developing governance mechanisms that ensure they have the level of professional competence needed to deal with dynamic environmental requirements.

This study also has implications for policymakers, pointing to the importance of public policy in stimulating environmental performance through investments in environmental R&D, hiring specialists with environmental capabilities, and collaborative projects among supply chain members (Chan *et al.*, 2018).

5.2 Limitations and avenues for future research

This study is not free from limitations. Regarding the database, the fact that this was a cross-sectional survey means that causality cannot be inferred; we thus recommend conducting future studies using longitudinal methodologies.

Moreover, our conclusions should be extrapolated with care, as they centre on a single economic sector. Although our findings can be of value to the Spanish tourism sector, future studies could attempt to check whether they apply to other sectors and countries.

With respect to the measurement instruments, the scales were based on managerial self-assessment. Admittedly, this technique has attracted criticism; that said, we believe our rigorous approach to data collection has helped address the problems associated with this methodology, as reflected in the reliability and validity measures.

In addition, the results obtained underline the need for future studies to explore a non-linear moderation effect of family ownership on the relationship between dynamic capabilities and environmental performance.

Future studies should also examine how the relationship between investment in dynamic capabilities and their impact on environmental performance is influenced by the heterogeneity of the family business in terms of its commitment to its stakeholders, its long-term orientation and its corporate governance and management structure.

References

Aiken, L.S., West, S.G. and Reno, R.R. (1991), *Multiple Regression: Testing and Interpreting Interactions*, Sage, Oaks, CA.

Albino, V., Dangelico, R.M. and Pontrandolfo, P. (2012), "Do inter-organizational collaborations enhance a firm's environmental performance? A study of the largest US companies", *Journal of Cleaner Production*, Vol. 37, pp. 304-315.

Albort-Morant, G., Leal-Millán, A. and Cepeda-Carrión, G. (2016), "The antecedents of green innovation performance: a model of learning and capabilities", *Journal of Business Research*, Vol. 69 No. 11, pp. 4912-4917.

Amui, L.B.L., Jabbour, C.J.C., de Sousa Jabbour, A.B.L. and Kannan, D. (2017), "Sustainability as a dynamic organizational capability: a systematic review and a future agenda toward a sustainable transition", *Journal of Cleaner Production*, Vol. 142, pp. 308-322.

Aragón-Correa, J.A. and Sharma, S. (2003), "A contingent resource-based view of proactive corporate environmental strategy", *Academy of Management Review*, Vol. 28 No. 1, pp. 71-88.

Bammens, Y. and Hünermund, P. (2020), "Nonfinancial considerations in eco-innovation decisions: the role of family ownership and reputation concerns", *Journal of Product Innovation Management*, Vol. 37 No. 5, pp. 431-453.

Barney, J.B. (1991), "Firm resources and sustained competitive advantage", *Journal of Management*, Vol. 17 No. 1, pp. 99-120.

Barros, I., Hernangómez, J. and Martin-Cruz, N. (2016), "A theoretical model of strategic management of family firms. A dynamic capabilities approach", *Journal of Family Business Strategy*, Vol. 7 No. 3, pp. 149-159.

Berrone, P., Cruz, C., Gomez-Mejia, L.R. and Larraza-Kintana, M. (2010), "Socioemotional wealth and corporate responses to institutional pressures: do family-controlled firms pollute less?", *Administrative Science Quarterly*, Vol. 55 No. 1, pp. 82-113.

Berrone, P., Cruz, C. and Gomez-Mejia, L.R. (2012), "Socioemotional wealth in family firms: theoretical dimensions, assessment approaches, and agenda for future research", *Family Business Review*, Vol. 25 No. 3, pp. 258-279.

Camisón, C. (2005), "On how to measure managerial and organizational capabilities: multi-item models for measuring distinctive competences", *Management Research: Journal of the Iberoamerican Academy of Management*, Vol. 3 No. 1, pp. 27-48.

Camisón, C. and Villar-López, A. (2014), "Organizational innovation as an enabler of technological innovation capabilities and firm performance", *Journal of Business Research*, Vol. 67 No. 1, pp. 2891-2902.

Campopiano, G. and De Massis, A. (2015), "Corporate social responsibility reporting: a content analysis in family and non-family firms", *Journal of Business Ethics*, Vol. 129 No. 3, pp. 511-534.

Carnes, C.M. and Ireland, R.D. (2013), "Familiness and innovation: resource bundling as the missing link", *Entrepreneurship Theory and Practice*, Vol. 37 No. 6, pp. 1399-1419.

Chan, E.S., Okumus, F. and Chan, W. (2018), "Barriers to environmental technology adoption in hotels", *Journal of Hospitality and Tourism Research*, Vol. 42 No. 5, pp. 829-852.

Charatsari, C., Kitsios, F., Stafyla, A., Aidonis, D. and Lioutas, E. (2018), "Antecedents of farmers' willingness to participate in short food supply chains", *British Food Journal*, Vol. 120 No. 10, pp. 2317-2333.

Chirico, F. and Salvato, C. (2016), "Knowledge internalization and product development in family firms: when relational and affective factors matter", *Entrepreneurship Theory and Practice*, Vol. 40 No. 1, pp. 201-229.

Chrisman, J.J. and Patel, P.C. (2012), "Variations in R&D investments of family and nonfamily firms: behavioral agency and myopic loss aversion perspectives", *Academy of Management Journal*, Vol. 55 No. 4, pp. 976-997.

Cohen, P., Cohen, J., West, S.G. and Aiken, L.S. (2003), *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd ed., Lawrence Erlbaum, Mahwah, NJ.

Cruz, C., Larraza–Kintana, M., Garcés–Galdeano, L. and Berrone, P. (2014), "Are family firms really more socially responsible?", *Entrepreneurship Theory and Practice*, Vol. 38 No. 6, pp. 1295-1316.

Dal Maso, L., Basco, R., Bassetti, T. and Lattanzi, N. (2020), "Family ownership and environmental performance: the mediation effect of human resource practices", *Business Strategy and the Environment*, Vol. 29 No. 3, pp. 1548-1562.

Dangelico, R.M., Pujari, D. and Pontrandolfo, P. (2017), "Green product innovation in manufacturing firms: a sustainability-oriented dynamic capability perspective", *Business Strategy and the Environment*, Vol. 26 No. 4, pp. 490-506.

Dangelico, R.M., Nastasi, A. and Pisa, S. (2019), "A comparison of family and nonfamily small firms in their approach to green innovation: a study of Italian companies in the agri-food industry", *Business Strategy and the Environment*, Vol. 28 No. 7, pp. 1434-1448.

Daspit, J.J., Long, R.G. and Pearson, A.W. (2019), "How familiness affects innovation outcomes via absorptive capacity: a dynamic capability perspective of the family firm", *Journal of Family Business Strategy*, Vol. 10 No. 2, pp. 133-143.

Dekker, J. and Hasso, T. (2014), "Environmental performance focus in private family firms: the role of social embeddedness", *Journal of Business Ethics*, Vol. 136 No. 2, pp. 293-309.

Diéguez-Soto, J., Manzaneque, M. and Rojo-Ramírez, A. A. (2016), "Technological innovation inputs, outputs, and performance: The moderating role of family involvement in management", *Family Business Review*, Vol. 29 No. 3, pp. 327-346.

Dillman, D.A. (1978), *Mail and Telephone Surveys: The Total Design Method*, Vol. 19, Wiley, New York, NY.

Duarte Alonso, A., Kok, S. and O'Brien, S. (2020), "Sustainable wine tourism development through the lens of dynamic capabilities and entrepreneurial action: an exploratory four-region perspective", *Tourism Recreation Research*, Vol. 45 No. 3, pp. 401-419.

Eikelenboom, M. and de Jong, G. (2019), "The impact of dynamic capabilities on the sustainability performance of SMEs", *Journal of Cleaner Production*, Vol. 235, pp. 1360-1370.

Felsberger, A., Qaiser, F.H., Choudhary, A. and Reiner, G. (2022), "The impact of Industry 4.0 on the reconciliation of dynamic capabilities: evidence from the European manufacturing industries", *Production Planning and Control*, Vol. 33 Nos 2-3, pp. 277-300.

Fernández, E., Junquera, B. and Ordiz, M. (2003), "Organizational culture and human resources in the environmental issue: a review of the literature", *International Journal of Human Resource Management*, Vol. 14 No. 4, pp. 634-656.

Fitz-Koch, S. and Nordqvist, M. (2017), "The reciprocal relationship of innovation capabilities and socioemotional wealth in a family firm", *Journal of Small Business Management*, Vol. 55 No. 4, pp. 547-570.

Forés, B. (2019), "Beyond gathering the 'low-hanging fruit' of green technology for improved environmental performance: an empirical examination of the moderating effects of proactive environmental management and business strategies", *Sustainability*, Vol. 11 No. 22, p. 6299.

Gómez-Mejía, L.R., Haynes, K.T., Núñez-Nickel, M., Jacobson, K.J. and Moyano-Fuentes, J. (2007), "Socioemotional wealth and business risks in family-controlled firms: evidence from Spanish olive oil mills", *Administrative Science Quarterly*, Vol. 52 No. 1, pp. 106-137.

Gomez-Mejia, L.R., Lannelongue, G., Muñoz-Bullón, F., Requejo, I. and Sanchez-Bueno, M.J. (2019), "Family firms' concern for the environment: does it pay off to pollute less?", *Academy of Management Proceedings*.

González-Cruz, T.F., Roig-Tierno, N. and Botella-Carrubí, D. (2018), "Quality management as a driver of innovation in the service industry", *Service Business*, Vol. 12 No. 3, pp. 505-524.

Graafland, J. (2020), "Family business ownership and cleaner production: moderation by company size and family management", *Journal of Cleaner Production*, Vol. 255, 120120.

Hair, J.F., Anderson, R.E., Tatham, R.L. and Black, W.C. (1998), *Multivariate Data Analysis*, 5th ed., Prentice-Hall, Englewood Cliffs, NJ.

Hang, M., Geyer-Klingeberg, J. and Rathgeber, A.W. (2018), "It is merely a matter of time: a meta-analysis of the causality between environmental performance and financial performance", *Business Strategy and the Environment*, Vol. 28 No. 2, pp. 257-273.

Hart, S.L. (1995), "A natural-resource-based view of the firm", *Academy of Management Review*, Vol. 20 No. 4, pp. 986-1014.

Hart, S.L. and Dowell, G. (2011), "Invited editorial: a natural-resource-based view of the firm: fifteen years after", *Journal of Management*, Vol. 37 No. 5, pp. 1464-1479.

Hayes, A.F. (2017), *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, Guilford Publications, New York, NY.

König, A., Kammerlander, N. and Enders, A. (2013), "The family innovator's dilemma: how family influence affects the adoption of discontinuous technologies by incumbent firms", *Academy of Management Review*, Vol. 38 No. 3, pp. 418-441.

Lado, A. A., Boyd, N. G. and Wright, P. (1992), "A competency-based model of sustainable competitive advantage: Toward a conceptual integration", *Journal of Management*, Vol. 18 No. 1, pp. 77-91.

Le Breton-Miller, I. and Miller, D. (2016), "Family firms and practices of sustainability: a contingency view", *Journal of Family Business Strategy*, Vol. 7 No. 1, pp. 26-33.

Leonidou, L.C., Leonidou, C.N., Fotiadis, T.A. and Aykol, B. (2015), "Dynamic capabilities driving an eco-based advantage and performance in global hotel chains: the moderating effect of international strategy", *Tourism Management*, Vol. 50, pp. 268-280.

Medase, S.K. and Abdul, S. (2021), "Trademark and product innovation: the interactive role of quality certification and firm-level attributes", *Innovation and Development*, Vol. 13 No. 1, pp. 1-41.

Memili, E., Fang, H.C., Koc, B., Yildirim-Öktem, Ö. and Sonmez, S. (2018), "Sustainability practices of family firms: the interplay between family ownership and long-term orientation", *Journal of Sustainable Tourism*, Vol. 26 No. 1, pp. 9-28.

Mousavi, S., Bossink, B. and van Vliet, M. (2018), "Dynamic capabilities and organizational routines for managing innovation towards sustainability", *Journal of Cleaner Production*, Vol. 203, pp. 224-239.

Naldi, L., Nordqvist, M., Sjöberg, K. and Wiklund, J. (2007), "Entrepreneurial orientation, risk taking, and performance in family firms", *Family Business Review*, Vol. 20 No. 1, pp. 33-47.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, p. 879.

Reyes-Santiago, M.D.R., Sánchez-Medina, P.S. and Díaz-Pichardo, R. (2019), "The influence of environmental dynamic capabilities on organizational and environmental performance of hotels: evidence from Mexico", *Journal of Cleaner Production*, Vol. 227, pp. 414-423.

Roscoe, S., Subramanian, N., Jabbour, C.J. and Chong, T. (2019), "Green human resource management and the enablers of green organisational culture: enhancing a firm's environmental performance for sustainable development", *Business Strategy and the Environment*, Vol. 28 No. 5, pp. 737-749.

Sakshi, S., Cerchione, R. and Bansal, H. (2019), "Measuring the impact of sustainability policy and practices in tourism and hospitality industry", *Business Strategy and the Environment*, Vol. 29 No. 3, pp. 1109-1126.

Samara, G., Jamali, D., Sierra, V. and Parada, M.J. (2018), "Who are the best performers? The environmental social performance of family firms", *Journal of Family Business Strategy*, Vol. 9 No. 1, pp. 33-43.

Shang, H., Chen, R. and Li, Z. (2019), "Dynamic sustainability capabilities and corporate sustainability performance: the mediating effect of resource management capabilities", *Sustainable Development*, Vol. 28 No. 4, pp. 595-612.

Sharma, P. and Sharma, S. (2011), "Drivers of proactive environmental strategy in family firms", *Business Ethics Quarterly*, Vol. 21 No. 2, pp. 309-334.

Singh, S.K., Chen, J., Del Giudice, M. and El-Kassar, A.N. (2019), "Environmental ethics, environmental performance, and competitive advantage: role of environmental training", *Technological Forecasting and Social Change*, Vol. 146, pp. 203-211.

Teece, D.J. (2007), "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance", *Strategic Management Journal*, Vol. 28 No. 13, pp. 1319-1350.

Teece, D.J., Pisano, G. and Shuen, A. (1997), "Dynamic capabilities and strategic management", *Strategic Management Journal*, Vol. 18 No. 7, pp. 509-533.

United Nations [UN] (2020), "The sustainable development goals report 2020", available at: https://unstats.un.org/sdgs/report/2020/ (accessed 18 March 2021).

Wang, Y., Chen, Y. and Benitez-Amado, J. (2015), "How information technology influences environmental performance: empirical evidence from China", *International Journal of Information Management*, Vol. 35 No. 2, pp. 160-170.

Wu, Q., He, Q. and Duan, Y. (2013), "Explicating dynamic capabilities for corporate sustainability: evidence from corporate social responsibility reports", *EuroMed Journal of Business*, Vol. 8 No. 3, pp. 255-272.

Zhu, Q. and Sarkis, J. (2007), "The moderating effects of institutional pressures on emergent green supply chain practices and performance", *International Journal of Production Research*, Vol. 45 Nos 18-19, pp. 4333-4355.

Supplementary material
The supplementary material for this article can be found online.

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Looking at the darker side of the mirror: the impact of CEO's narcissism on corporate social irresponsibility

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Received 14 September 2022
Revised 25 April 2023
Accepted 7 July 2023

Abstract

Purpose – The aim of this article is to highlight the major part played by executives in the escalation of corporate social irresponsibility (CSI). Based on the upper echelons theory, the authors developed a model which shows the essential role of CEOs in explaining CSI. The authors proposed that the key personality traits of CEOs—narcissism—, as well as their power, could explain the degree of CSI.

Design/methodology/approach – Due to the significant methodological challenges when investigating CSI, the authors explored a novel method for measuring CSI in order to assess the degree of irresponsible behaviors. The authors build a CSI scale based on the perceptions of key informants, i.e. experts with diverse professional backgrounds. The authors apply CSI scale in a sample of 84 Spanish companies that were involved in CSI.

Findings – The results of the authors' empirical study show the positive and significant influence of CEO narcissism and CEO power on the degree of CSI.

Research limitations/implications – On the one hand, corporate irresponsibility scandals have relevant social consequences and practical implications. On the other hand, narcissism is a natural feature of managers in top positions that is increasing in societies.

Practical implications – The authors' findings may help CEOs, TMTs and corporate boards to acknowledge potential sources of CSI decreasing its likelihood through counterbalancing CEO's power and considering the dark side of narcissism.

Social implications – On the one hand, corporate scandals have relevant social and practical implications. On the other hand, narcissism is a natural feature of managers in top positions that is increasing in societies.

Originality/value – In this paper, the authors highlight the role of CEOs characteristics and their firms as the key actors for explaining and understanding the degree of CSI.

Keywords Corporate social irresponsibility, CEO, Narcissism, Power, Upper echelons theory

Paper type Research paper

Introduction

Corporate social irresponsibility (CSI) and the associated corporate scandals—e.g. the cases of Enron, Petrobras, World.com, Bankia or Volkswagen—have not stopped in this century. CSI, —i.e. corporate acts that intentionally cause harm (Clark *et al.*, 2022; Kemp and Owen, 2022) —has relevant social, environmental and economic consequences impacting companies, communities and people worldwide. As Iborra and Riera (2023) state, there is empirical evidence that CSI provoked enormous consequences, between others, in

This work has received financial support from Generalitat Valenciana AICO/2021/309.

European Journal of Management and Business Economics
Vol. 34 No. 1, 2025
pp. 67-87
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-09-2022-0289

consumers–in emotions, attitudes or purchase intentions–(e.g. Antonetti, 2020; Valor *et al.*, 2022), in firms' financial performance as well as in firms' reputation, trustworthiness and moral capital (e.g. Sun and Ding, 2021; Wang and Li, 2019), in firm's transaction costs (Feng *et al.*, 2022) and in workplace deviant behaviors as a form of employee revenge (Abbasi and Amran, 2023). These important and far-reaching consequences may explain the increased interest of researchers and practitioners in understanding CSI antecedents [1].

In respect to CSI antecedents, researchers tend to see CSI as a matter of "*good firms in bad context*" (Cuervo-Cazurra *et al.*, 2021). They focus on institutional level antecedents in the home or host countries that may encourage irresponsible practices [2] (Boudier and Bensebaa, 2011; Matten and Moon, 2005, 2008; Surroca *et al.*, 2013) as if internal factors were irrelevant. However, the scandals cited above have shown the significant part played by the firms' CEOs J.Skilling—Enron—, A.Bendine—Petrobras—, B.J.Ebbers—Worldcom—, R.Rato—Bankia— or O.Schmidt—Volkswagen, opening the question of which CEOs may be more likely linked in volitional and, to some degree, planned irresponsible acts.

In order to answer this question, we rely on upper echelons theory, focusing on CEOs as the key actors that shape firms' behaviors and actions and, in this research, acts of CSI (Hambrick and Mason, 1984). The upper echelons theory proposes that strategic decisions are connected to the background characteristics of management. In that sense, it is suggested that in order to understand the way companies behave, it is necessary to study certain characteristics, experiences and cognitive values of their upper echelons (Finkelstein *et al.*, 2009; Hambrick and Mason, 1984).

In that sense, CSI considers that irresponsible behavior is linked to fails in being aware of undesirable effects of firm decisions or to take proper care of something or lack regard for the consequences of their actions (Godfrey, 2005). So, we argue in this research that CEOs traits linked to the failure of regard for others, selfishness or greed may act as antecedents of CSI.

Scholars in the field of management state that narcissism is a personality trait which is characterized by encompassing self-admiration, self-absorption, authority, exhibitionism, superiority, arrogance, exploitation of others, self-sufficiency and extreme vanity (Emmons, 1987; Rijsenbilt and Commandeur, 2013). Due to these features, narcissistic individuals seem prevalent in top management positions. In this line, for example, Rovelli and Curnis (2021) demonstrate that narcissistic individuals tend to become CEOs earlier in their professional careers, being stars. Their relevance in top management positions—and its increase in the society in young generations (Young *et al.*, 2016)—has attracted the attention of researchers (Campbell *et al.*, 2011; Cragun *et al.*, 2020; Rovelli and Curnis, 2021; Rovelli *et al.*, 2023; Salehi *et al.*, 2020; Tang *et al.*, 2018) about its causes, characteristics and consequences. In respect to the latter, Kim *et al.* (2018, p. 204) stated that "Narcissism is a multifaceted concept characterized by a positive and inflated view of the self and a self-regulation strategy that manages and aggrandizes this positive view of the self". This effect of narcissism has a bright side [3]; but, narcissism, has also been associated with other characteristics such as the need for constant applause, a manipulative nature, a high level of selfishness and, which is particularly relevant for our study, a lack of concern and empathy for the interests and expectations of third parties (Campbell and Foster, 2007; Chatterjee and Pollock, 2017; Myung *et al.*, 2017; Nevicka *et al.*, 2011). We argue that this lack of concern regarding the consequences of their actions and behavior for others allow us to propose a link between CEO's narcissism and CSI, showing the darker side of the mirror [4]. Additionally, we argue that the context of CEO decision-making may impact CSI; specifically, the centralization of power in the CEO instead of sharing power at the firm's upper echelon may impact CSI because other points of view and different interests may not be taken into account.

Our study makes several contributions to the research on CSI antecedents by investigating the role played by upper echelons in this type of behavior. In respect to CSI growing research, we help to fill an underdeveloped line of research that links individual level

antecedents with CSI behaviors (Iborra and Riera, 2023; Grijalva and Harms, 2014). By focusing on the individual level instead of on institutional variables, we respond to the call made by Ghoshal (2005, p. 79): "when managers, including CEOs, justify their actions by pleading powerlessness in the face of external forces, it is to the dehumanization of practice that they resort. When they claim that competition or capital markets are relentless in their demands, and that individual companies and managers have no scope for choices, it is on the strength of the false premise of determinism that they free themselves from any sense of moral or ethical responsibility for their actions". We argue and provide evidence that CEOs are the key actors influencing CSI. We contribute also to upper echelons theory, specifically analyzing the impact of narcissism, which is one of the traits of upper echelons, on CSI and providing new evidence of the dark side of this trait. Finally, our study draws attention to CSI as a construct that is distinct from corporate social responsibility (CSR) and has its own antecedents [5] that calls for special consideration (Clark *et al.*, 2022; Iborra and Riera, 2023) [6]. In this line, we explore a novel method for measuring the degree of CSI as a specific construct. Concretely, we construct a scale of CSI degree based on the perceptions of a panel of experts belonging to different groups of stakeholders.

In the next section, we review the literature and present our hypotheses. After describing our research method, we present our empirical findings, which derive from data on 84 Spanish companies. We conclude with a discussion of the results, together with their implications and issues for further research.

CSI and the role of CEOs

While Armstrong (1977) was a pioneer in introducing the CSI concept in the academic literature, it has been the last 20 years when academia has devoted notable attention to it (Riera and Iborra, 2017; Clark *et al.*, 2022). CSI focuses on the harmful consequences of an act and definitions include acts causing harm, hurting, causing damage or violation with different degrees (Clark *et al.*, 2022) that can go from the loss of human life, to the loss of nonhuman life or to the loss of livelihoods in local communities (Mena *et al.*, 2016; Clark *et al.*, 2022). Additionally, CSI focuses on the organization or the corporation as an *actor*. Corporations as collective agents because they are capable of intentional actions, having specific decision procedures that help to explain how they reach decisions and how they act. In that sense, Godfrey's (2005, p. 787) states that "bad acts must be accompanied by a bad mind" incorporating intention to the definition and giving place for the role of the two core issues in CSI: damage and intention (Clark *et al.*, 2022). So, we consider that a company is involved in CSI if it intentionally causes damage or harm to others [7]. This definition fits with researchers that advocate for considering that CSI is a different construct from CSR deserving individual attention (Strike *et al.*, 2006; Riera and Iborra, 2017; Clark *et al.*, 2022).

In understanding CSI antecedents, scholars have primarily studied antecedents at environmental level. For example, how institutional context and government corruption influences the occurrence of CSI (Ashforth and Anand, 2003; Keig *et al.*, 2015). CSI is seen as a matter of good firms in bad contexts, resulting from poorly regulated settings and weak institutions—external antecedents—rather than from "bad" firms and managers—internal antecedents— (Cuervo-Cazurra *et al.*, 2021).

Contrary to this trend, the upper echelons theory (Hambrick and Mason, 1984) suggests that CEO characteristics, experiences and cognitive values should be studied in order to understand the actions of companies, since CEOs play a key role in decision-making and, therefore, to explain company results, strategic decisions and behaviors. Recently, some articles open this line of research linking the upper echelons theory with CSI. Specifically, they focus on well-known demographic characteristics, such as CEOs' tenure or career horizons, as antecedents of CSI (Lee *et al.*, 2018; Oh *et al.*, 2018).

We delve in this line of research. We argue that given that irresponsibility is an issue closely linked with ethics, values and personal beliefs (Carroll, 1979), certain CEO psychological features may directly influence moral and ethical aspects and hence also irresponsibility issues (Garriga and Melé, 2004). Psychological features are made up of values, cognitive models and other elements of the personality, with which executives filter and interpret both external and internal stimuli. There is evidence that CEOs' values, together with the attitude and awareness of CEOs concerning these issues, increase the likelihood of having a significant influence on CSR results (Laguir *et al.*, 2016; Waldman and Siegel, 2008). In this regard, Waldman and Siegel (2008) point out that if CEOs have a strong ethical conviction, this contributes to positive results in CSR. In the same vein, Laguir *et al.* (2016) have shown that one of the key factors for adopting CSR lies in the commitment of CEOs, as well as in their values and culture.

In the case of CSI, we argue that CEOs' psychological features will affect the way in which executives filter and interpret information, demands and interest (Andreoli and Lefkowitz, 2009). Even more, regarding psychological characteristics, irresponsibility is related to causing harm to stakeholders, so it involves a behavior where there is a lack of consideration regarding the interests and expectations of stakeholders, as well as a lack of empathy and selfishness. Consequently, we argue that CEO narcissism, i.e. arrogance, selfishness and feelings of superiority could predict the likelihood of CSI.

CEO narcissism and its link with CSI

Upper echelons researchers highlight that CEO narcissism helps to understand decision-making processes (Chatterjee and Hambrick, 2007; Cragun *et al.*, 2020; Tang *et al.*, 2018).

Ellis (1898) first introduced the concept of narcissism in the field of psychology when alluding to the Greek myth of the young Narcissus, who falls in love with his own reflection in the water. However, this concept grew stronger thanks to the Austrian neurologist, Sigmund Freud (1957). He stated that leaders only need their own love and are usually extremely selfish, self-confident and independent (Freud, 1957). Two decades later, narcissism was considered as a personality disorder (Raskin and Hall, 1979). It was only in 1994, however, when the American Psychiatric Association considered narcissism not only as a clinical disorder but also as a dimension of personality. Therefore, narcissism has been studied under a double perspective, i.e. as a personality disorder (psychiatric feature) and as a personality trait.

In the management literature, Campbell *et al.* (2011, p. 269) in their review, define narcissism as containing three components, "First, the narcissistic self is characterized by positivity, "specialness" and uniqueness, vanity, a sense of entitlement and a desire for power and esteem. Second, narcissistic relationships contain low levels of empathy and emotional intimacy … Third, there are narcissistic strategies for maintaining inflated self-views". For management scholars, narcissistic CEOs are characterized by having traits such as self-admiration, self-absorption, authority, exhibitionism, feelings of superiority, arrogance, exploitation of others, self-sufficiency and extreme vanity (Emmons, 1987; Rijsenbilt and Commandeur, 2013; Kim *et al.*, 2018; Cragun *et al.*, 2020).

In fact, it is considered as a key personality trait to explain corporate outcomes (Campbell *et al.*, 2011; Chatterjee and Hambrick, 2007; Oesterle *et al.*, 2016; Cragun *et al.*, 2020; Seifzadeh *et al.*, 2021) and is a psychological trait of most executives of important global companies (Finkelstein *et al.*, 2009; Kim *et al.*, 2018). In this sense, narcissism has been studied as a feature that lies at the heart of leadership and "anyone who hopes to the rise to the top of an organization should have a solid dose of narcissism" (de Vries, 2004, p. 188).

However, in the debate on the pros and cons associated with narcissism empirical findings are contradictory (Chatterjee and Hambrick, 2007; Maccoby, 2000; Salehi *et al.*, 2022). Cragun

et al. (2020) in their meta-analysis of 37 studies found a positive and significative effect of narcissism over financial performance [8], mixed results for innovation and growth and no significant ones for risk-taking. Even more, to date, no consensus has been reached as to how narcissism affects the performance of companies (Anninos, 2018). Seifzadeh *et al.* (2021) empirically studied that there is a positive and significant relationship between CEO narcissism and overconfidence and real earnings management and managers' myopia and financial statements readability. In their own words, "Managers may use our results to improve their capabilities, such as their accuracy in preparing financial statements, through working on their personal features" (Seifzadeh *et al.*, 2021, p. 123).

In terms of the socially responsible effects, although narcissism has been increasingly considered in the literature as an important factor when developing CSR strategies (Kim *et al.*, 2018; Petrenko *et al.*, 2016), there is also no agreement regarding how narcissism affects CSR.

On the one hand, a few studies have suggested that narcissistic CEOs, due to their charisma and self-esteem, have a positive impact on company results, because they assume more efficient leadership roles and, consequently, obtain greater business benefits (Deutschman, 2005). In this vein, Salehi *et al.* (2022) found evidence for the impact of CEOs and TMTs narcissism on firms' relative performance. Campbell *et al.* (2004) highlight that narcissistic personalities are characterized by the use of strategies which improve and preserve their own positive image. They have a need for constant admiration and attention from others, which positively influences the company's results (Bogart *et al.*, 2004). In this sense, narcissistic CEOs can become the center of attention and be socially admired through CSR: as corporate socially responsible activities are likely to involve a facet of the CEO's positive self-image and to bring positive attention to the CEO (Petrenko *et al.*, 2016). Consequently, more narcissistic CEOs are likely to carry out CSR actions since they see CSR as "an opportunity to enhance their own positive self-image by pursuing socially desirable activities" (Kim *et al.*, 2018, p. 206). In this line, Tang *et al.* (2018) in a sample of 235 USA firms from S&P 1500 found support for the positive effect of narcissism over CSR while moderated by their industry peers' behaviors in terms of higher/lower investment in CSR. They argue and obtain evidence that narcissist CEOs need constant applause and attention to affirm their inflated positive self-view that can be obtained through CSR.

On the other hand, Petrenko *et al.* (2016) provide a different view of how narcissism impacts social responsibility. Narcissistic CEOs may hide or avoid showing certain behaviors so as not to lose their reputation; i.e. they use strategies to divert attention from harmful or risky behavior (Buss and Chiodo, 1991; Surroca *et al.*, 2013). Thus, although narcissistic CEOs possess good skills to be efficient managers and can even achieve positive results for their companies, their narcissistic personality can cause harm to their businesses in the long term (Lister, 2004). Campbell *et al.* (2011) also stated that although narcissistic CEOs are self-confident, extroverted, charming and seek attention and applause, they do not feel empathy and show an abusive, arrogant and dominant behavior. Chatterjee and Hambrick (2007) point out that narcissistic executives are also prone to be sensitive to criticism and threats and are highly competitive, which is counterproductive especially for their stakeholders–employees, clients, suppliers, society, etc.—(Anninos, 2018). In this line, O'Reilly *et al.* (2018) provide evidence that narcissistic CEOs deny others opinion. In their study, narcissistic CEOs are positively related to enter into lawsuits and long litigations and avoiding the opinion of experts about their potential success.

Other scholars have also analyzed how the manipulative and insensitive nature of narcissistic CEOs influences their decision-making, in that materialism is a crucial aspect for understanding the relationship between narcissism and CSI. Materialism is an intrinsic value of narcissistic people, which predisposes them to focus on obtaining personal profits and gains, even transferring company profits to their own benefit (Campbell and Foster, 2007). This suggests that narcissistic top managers do not prioritize stakeholder concerns and

interests, but concentrate solely on their own expectations (Wales *et al.*, 2013). Narcissistic CEOs are characterized by materialism, making them prone to derive the maximum profit to the detriment of the needs and expectations of their stakeholders (Chatterjee and Pollock, 2017). As Cragun *et al.* (2020) state in their review, the definitions of narcissism include a general lack of regard for others and it "refers to a lack of empathy toward others and a tendency to exploit situations and persons for personal gain".

In respect to specific stakeholders, several scholars have stressed how narcissism in CEOs causes damage to employees and other organization members (Abbasi and Amran, 2023; Campbell and Siedor, 2016). In fact, Judge *et al.* (2006) showed that narcissism is positively linked with intentional damage in workplaces. Similarly, Chen *et al.* (2013) concluded that narcissism exacerbates the effects of incivility in workplaces, while Nevicka *et al.* (2011) consider that narcissism also influences the information exchange at the group level, which may be detrimental for employee interests and expectations. In this line, Grijalva and Harms (2014) suggest that narcissistic CEOs are related with counterproductive work conduct, aggressiveness and leadership egoism. Therefore, it seems reasonable to believe that narcissistic CEOs lack the capability to socialize and to understand their stakeholders, creating a toxic work environment, which may have a negative effect on the interests and expectations of stakeholders (Grijalva and Harms, 2014).

In summary, we argue that narcissistic CEOs decision-making may take into account solely their own interests and not those of third parties, as well as ignoring the information received from others. Moreover, they lack empathy and disregard the concerns expressed by other stakeholders increasing the likelihood of ignoring the interests of third parties and ignoring the harmful consequences this behavior can cause. Based on the above arguments, we propose the following hypothesis:

H1. The higher the degree of CEO narcissism, the greater the degree of CSI.

CEOs' centralized power and CSI

CEO characteristics help to understand firms' actions; however, their influence may vary with the centrality of CEOs in decision-making processes. As the upper echelons theory states, CEO power can be centralized at the apex or it can be shared and it can be more or less monitored and controlled by the board of directors (BoD) (Finkelstein *et al.*, 2009). The relationship between CEO characteristics and CSI may change with the degree to which the CEO centralizes power or, conversely, shares power with other members (Pitcher and Smith, 2001). Pearce (1997) stresses that decentralized power mitigates uncivil behaviors in the members of a company.

When decision-making and power is shared between CEO and BoD, there is access to more information and a wider network where the concerns of stakeholders can be made known. Consequently, there is a greater probability of optimally satisfying stakeholder needs. In that sense, Shafeeq Nimr Al-Maliki *et al.* (2023) evidence the role of the board in providing information and monitoring in relation to CSR. As Pearce and Manz (2011) consider, individualized decision making will not be aligned with the objectives, interests or needs of the rest of the company members.

CEOs who centralize decision-making are characterized by a minimal predisposition to sharing responsibility with other people and this centralized power may favor using their influence to behave corruptly (Pearce *et al.*, 2008). The limited power of the board will not allow monitoring CEOs behavior and controlling its actions and consequences. Likewise, centralization of power means that there are fewer individuals who hold power in decision-making, and thus there would be fewer consensuses in a group (Wong *et al.*, 2011). In this type of power structure, one of the problems that companies have to face is the feeling that most employees consider themselves as being "outside" of the decision-making processes, since

they do not regard themselves as participants in these processes in the companies where they carry out their professional lives. As a result, they feel demotivated when it comes to sharing the points of view and opinions of the interest groups with which they interact.

We argue that the centralization of decision-making in a powerful CEO would be related to an absence of heterogeneity and diversity regarding the different interests and will not allow taking into account other points of view. In contrast, more diversity helps to understand the needs and desires of the different interest groups, because their characteristics reflect the wishes and preferences of society (Ayuso and Argandoña, 2007). Brammer *et al.* (2007) consider that decentralization promote consensual decision-making, respect for inclusion of the interests of people with different expectations, which helps to avoid CSI.

Therefore, we consider that power centralization in CEOs will be related to CSI.

H2. The higher the degree of power centralized in a CEO, the greater the degree of CSI.

Methodology

Sample and data collection

We use secondary sources to select the companies in our study. Through the Factiva database and Google's search tool, *Google News,* we draw a sample of the Spanish companies [9] that had caused harm to social, economic or/and environmental dimensions and were being investigated, accused of and/or convicted of crimes in the Spanish Penal Code during the period from 2005 to 2012 [10]. The key terms [11]: *corruption, *fraud, *bribery, *money laundering, *misappropriation of funds, *false accounting, *false statements *severe labor exploitation, *sexual harassment, *ecological disasters, *environmental disasters, *illegal financing of political parties * urban crime, *tax evasion, * prevarication, * corporate crime; additionally, we also included companies condemned by the Spanish antitrust court for anti-competitive behaviors identified by the Spanish antitrust law [12]. The search resulted in a preliminary sample of 256 companies.

We then identify the CEOs of the preliminary sample. The names and surnames of CEOs were obtained from Bureau Van Dijk' Orbis database, company's website or online news and their profile was obtained through LinkedIn. The final sample was made up by 84 companies.

In our sample, 70% of the companies are SMEs [13]. With respect to industries, 37% belong to the manufacturing industry, while 63% are service companies. In the sample, 42.9% of the companies are condemned for only one irresponsible behavior, 13.1% are involved in five or more and 44.1% are linked to two to five irresponsible behaviors. In the case of firms condemned for only one irresponsible behavior, in 66.7% of the cases, this behavior lasted for two years or more (in 27.8% for five years or more).

Variables definition

Dependent variable: degree of CSI. The sample selection includes companies involved in CSI: they intentionally caused harm to others in different degrees. In order to evaluate the degree of CSI ,we follow Armstrong (1977) definition and focus on the perceptions of impartial experts/observers. We focus on ranking the offense itself, e.g. sexual harassment or ecological offense and not on ranking the specific firms. We selected a diverse group of experts [14] in management and law who helped us with their informed opinion, knowledge and experience in these fields (Skjong and Wentworth, 2001). Seventeen experts participated in this study (see Table 1), all of whom were asked to rank the degree of irresponsibility of the different criminal offenses stipulated in the Spanish Penal Code. According to their professional background, the experts belong to three different groups, since CSI can be perceived differently [15]. In this line, people with similar characteristics evaluate the same issue in a similar way (Tajfel, 2010).

Indicator	Description	Professional background	Educational background	Gender	Age (years)
E1	Judges and prosecutors, experts in the application of penal law at high criminal offenses level	District Chief Court Instance in Spain	Graduated in Law and Business	Female	<40
		Anti-drug prosecutor in Spain	Graduated in Law	Female	>55
		Crime unity prosecutor in Spain	Graduated in Law	Female	<40
		District Chief prosecutor in Spain	Graduated in Law	Male	<40
		Constitutional Court prosecutor in Spain	Graduated in Law	Male	>55
		Magistrate of the Valencia Provincial Court. President of the anticorruption platforms	Graduated in Law	Male	>55
E2	Managers and other experts in corporate decision making and consulting	Professor of Strategic Management	Graduated in Business	Male	>55
		Full professor of Strategic Management	Graduated in Business	Female	41–54
		Founder and CEO of a Consulting firm	Graduated in Business	Male	>55
		Strategic consultant	Industrial engineer	Male	<40
		CEO of a Spanish multinational company	Telecom engineer	Male	<40
		TMT of a private company	Graduated in Law	Male	41–54
		United Nations employee at Latin America	Graduated in Law and Political Science	Female	<40
E3	Lawyers experts in areas related to firms' criminal offenses	Full professor of Criminal Law	Graduated in Law	Female	41–54
		Full professor of Urban Planning Law and lawyer	Graduated in Law	Male	>55
		Lawyer and official of Valencia antitrust Council	Graduated in Law	Female	>55
		Lawyer and full professor	Graduated in Law	Female	41–54

Source(s): Table by the authors

Table 1. Experts' characteristics

The perceptions from the unbiased experts were collected through a questionnaire, which contained the types of criminal offenses under review with information about their corresponding legal penalties. Each expert assigned a score, from 1 to 5, to each criminal offense according to their perception of its severity, assigning 1 to less severe criminal offenses and 5 to more severe criminal offenses. The average of the scores of each criminal offense by each group of experts was the optimum solution for measuring their answers.

Prior studies (Keig *et al.*, 2015; Strike *et al.*, 2006) have measured CSI through the Kinder, Lydenberg, Domini Research and Analytics database [16]. It considers an overall CSI score that results from adding up a set of binary indicators of concerns from a wide range of CSR dimensions [17]. In addition, it does not allow measuring properly the degree of harm (concerns are added as each dimension has the same impact). Our proposal is a first step in

evaluating the degree of harm or offense caused by an act and in distinguishing the harm from the firm causing itthat usually will contaminate the evaluation of the act through firm's image and reputation.

Independent variables. Narcissism. The measurement of narcissism through primary sources is difficult, since heads of companies are reluctant to answer questions regarding narcissism (Cragun *et al.*, 2020). In this sense, Chatterjee and Hambrick (2007) were pioneers in creating a narcissism scale based on secondary sources of information. This scale is made up of five indicators and is widely used in the literature (Cragun *et al.*, 2020; Oesterle *et al.*, 2016). Nonetheless, researchers have recently made an effort to adapt Chatterjee and Hambrick's (2007) narcissism scale to private small and medium companies. In this line, Aabo and Eriksen (2018), have adapt the narcissism scale, using indicators from LinkedIn profiles. Since 65% of our samples are small and medium companies, we followed this approach and used LinkedIn as a source of information to obtain data to measure CEO narcissism. So, adapted from Chatterjee and Hambrick's (2007) and Aabo and Eriksen's (2018) our scale relies on four indicators: (1) skills and endorsement sections, (2) previous job positions, (3) LinkedIn photographs and (4) resume sections (see Table 2).

Indicator	LinkedIn section	Connection with narcissism
N_1	Skills and endorsements sections. Contacts can validate these skills and users must be approved it to appear in their profiles	This section reflects the CEO's willingness and narcissistic features. As constant applause and attention (Bogart *et al.*, 2004)
N_2	Previous job positions. Majority of the company CEOs must have a large amount of previous positions	The list of number of job positions is important to determine the degree of narcissism, offering an exhaustive description of the arrogance of them (Aabo and Eriksen, 2018)
N_3	LinkedIn photography, as a similar meaning of CEO photography in annual reports	The inclusion of a photography oneself is an indicator of narcissism since reflects vanity (Chatterjee and Hambrick, 2007)
N_4	Summary section. It is a voluntary section containing skills, personal information, hobbies, interests (Aabo and Eriksen, 2018)	This indicator reflects the user narcissism since details a superiority need and arrogance (Chatterjee and Hambrick, 2007)

Source(s): Table by the authors

Table 2.
Indicators of CEO narcissism at LinkedIn

Each indicator is a dichotomous variable, where (0) reflects the absence of the indicator in the LinkedIn profile and (1) reflects the presence of the indicator in the LinkedIn profile.

CEO power. The centralization of CEO power was measured through three indicators which reflect the structure of the board of directors and its distribution of power: (1) the existence of a unique administrator or a solidary administrator versus the existence of a BoD [18], (2) the duality of responsibilities in the BoD, where the roles of CEO and chair of the board are taken on by the same person and (3) ownership control [19] where one individual shareholder has more than 51% of the shares. These three elements are crucial for understanding the relationship between the board's structure and CEO power and discretion (Finkelstein *et al.*, 2009).

Control variables. Several other variables can potentially influence CSI. Following the upper echelons theory, we use three control variables that are related to the behavior of the CEO: the diversity of the board in terms of the percentage of gender diversity and international diversity and the counterbalance role of family ownership in CEO behavior.

Family business scholars agree that family-owned firms are known for their interest in protecting and preserving their socio-emotional wealth (hereinafter "SEW") (Gómez-Mejía *et al.*, 2014). Furthermore, family-owned firms are driven by the need to reinforce the legacy of the family's SEW and continuously seek the support and approval of their interest groups

(Berrone *et al.*, 2010). Berrone *et al.* (2010) stated in their empirical study that family-owned firms are less likely to contaminate the environment, their aim being to protect their SEW and lessen the damage to their stakeholders.

We also control for two demographic characteristics regarding the diversity in the board composition. Together with board structure, board composition is a key dimension for understanding its decision- making (Finkelstein *et al.*, 2009). For this reason, we control for gender diversity as the percentage of women on the board as well as for international diversity as the presence of different nationalities on the board because these characteristics can be linked to being more open to different points of view, perspectives and interests, which is enriching (Finkelstein *et al.*, 2009).

Data analysis

Measurement model validation

The structural model depicted in Figure 1 was estimated by means of the Partial Least Square Path Modeling (PLS-PM) using SmartPLS 4.0 (Ringle *et al.*, 2022). This approach has minimal demands regarding sample size, relaxes the assumption of multivariate normality needed for maximum likelihood-based structural equation modeling (SEM) estimations and is suitable for applications where strong assumptions cannot be fully met (Hair *et al.*, 2012).

Measurement model properties were evaluated according to the recommendations of Hair *et al.* (2012) for PLS-PM. We analyzed the reliability, convergent validity and discriminant validity of the measurement model. In respect to internal individual consistency, Table 3 shows that all indicators are significantly associated with their respective constructs ($p < 0.01$) and their individual standardized loadings are greater than 0.70 or their mean is greater than 0.70 [20] (Bagozzi and Yi, 1988; Chin, 1998), which shows that these indicators are highly reliable. Internal consistency reliability was examined via Cronbach's alpha (CA) and composite reliability (CR). All constructs had CA values above 0.7 and their CR values are superior to 0.83 and all were greater than the threshold of 0.7 (Bagozzi and Yi, 1988).

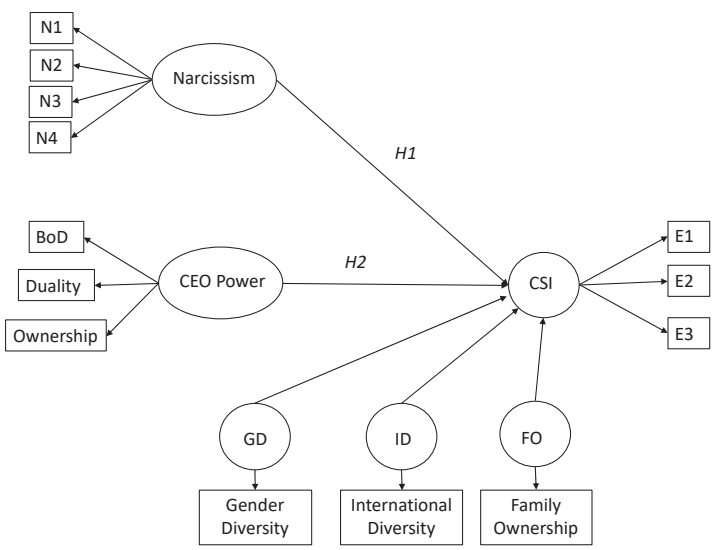

Figure 1.
Proposed model

Source(s): Figure by author

In respect to convergent validity, it allows measuring if all the items measure the same construct. The average variance extracted (AVE) for each construct was higher than the 0.50 threshold (Fornell and Larcker, 1981), which confirms the convergent validity of the measurement model. Through 5,000 bootstrap samples and a number of cases equal to the 84 valid observations of the original sample, we analyzed the size of the standardized loadings and all were significant at $p < 0.01$.

Discriminant validity states that constructs involved in the analysis are measuring different realities. Table 4 shows first criteria of discriminant validity. It was assessed by checking that the correlation between each pair of constructs was smaller than the square root of the AVE of the implied constructs (Fornell and Larcker, 1981). Supporting this conclusion, Table 4 shows the HTMT ratios, proposed by Henseler *et al.* (2015). They are always lower than 0.90 which provides additional discriminant validity to our measures, i.e. relations between indicators belonging to a same construct (Monotrait heteromethod-MT) are higher than the ones with different constructs (Heterotrait heteromethod-HT).

In sum, the measurement model has reliability, convergent validity and discriminant validity.

Variables	Indicators	Standardized loading	*t*-value (bootstrap)	CA	CR	AVE
CSI	E1	0.875	17.563	0.888	0.931	0.817
	E2	0.917	30.245			
	E3	0.920	31.333			
CEO narcissism	N1	0.875	7.199	0.796	0.859	0.605
	N2	0.754	4.559			
	N3	0.674	3.475			
	N4	0.795	6.072			
CEO power	BoD	0.766	3.555	0.726	0.839	0.636
	Duality	0.849	4.225			
	Ownership control	0.774	3.459			
Family ownership control	FO	1.000	–	1.000	1.000	1.000
Gender BoD diversity	Gender	1.000	–	1.000	1.000	1.000
International BoD diversity	Internet	1.000	–	1.000	1.000	1.000

Note(s): All loadings are significant at $p < 0.01$ level. CA= Cronbach's alpha; CR = Composite reliability; AVE = Average variance extracted
Source(s): Table by the authors

Table 3. Measurement model. Reliability and convergent validity

	1	2	3	4	5	6
1. CEO narcissism	*0.778*	0.251	0.218	0.249	0.194	0.293
2. CEO power	−0.131	*0.797*	0.720	0.244	0.379	0.249
3. Family ownership	−0.193	0.583	*1.000*	0.259	0.384	0.039
4. Gender diversity BoD	0.190	−0.211	−0.259	*1.000*	0.025	0.113
5. International diversity BoD	0.063	−0.296	−0.384	−0.025	*1.000*	0.056
6. CSI	0.282	0.214	0.027	0.108	−0.041	*0.904*

Note(s): On the diagonal: square root of AVE. Below the diagonal: correlations between latent variables. Above the diagonal: HTMT ratios
Source(s): Table by the authors

Table 4. Measurement model discriminant validity

Structural model evaluation

We first analyzed internal collinearity of the constructs of our analysis. Table 5 provides the inner VIF values. All of them are lower than five which reveals no collinearity problems (Hair *et al.*, 2012).

To test our model hypotheses, the t-values of the path coefficients used to establish path significance were obtained by applying nonparametric bootstrapping. Following Hair *et al.*'s (2012) recommendation, we selected 5,000 bootstrap samples and a number of cases equal to the 84 valid observations of the original sample. Regarding the PLS-PM algorithm settings, individual sign changes were allowed, and a uniform value of 1 was set as an initial value for each of the outer weights.

Table 6 summarizes our results. In terms of direct effects, CEO narcissism does have a significant effect on CSI ($\beta = 0.336$; $p < 0.05$; $f^2 = 0.09$). Thus, we find evidence to support Hypothesis 1. The standardized path coefficient is higher than 0.3 showing a strong relationship between CEO narcissism and CSI (Chin, 1998).

Additionally, CEO power has a significant effect on CSI ($\beta = 0.303$; $p < 0.01$; $f^2 = 0.08$), which confirms Hypothesis 2. The standardized path coefficient is higher than 0.3 showing a strong relationship between CEO power and CSI (Chin, 1998).

None of the control variables were significant. Table 6 shows the hypothesis testing results.

In terms of the total variance explained, the predictive capacity of the model, as measured by adjusted R^2, was of 10.5%. Predictive relevance of the model was tested using Stone–Geisser's Q^2 statistic (Geisser, 1974; Stone, 1974), which was obtained via blindfolding with an omission distance of 10. According to Stone (1974), this criterion is adequate if Q^2 is positive. Our Q^2 is 0.101 showing predictive relevance of the relationships between the variables. Power analysis was performed using G*Power 3.1 (Faul *et al.*, 2009), to test whether our sample size guaranteed enough power for the R^2 deviation from zero test which was greater than 85%.

Additional analysis

We conducted some checks to confirm the robustness of our results. To assess construct validity in our measurement of the degree of CSI, we first correlated the overall CSI measure ($\alpha = 0.88$) with a measure of the degree of harm based on the proposal of Clark *et al.* (2022) and

	CSI
CEO power	1.541
Family power	1.728
Gender	1.126
International diversity	1.211
Narcissism	1.062

Table 5. Inner VIF values

Source(s): Table by the authors

Hypothesis	Path	Standardized path coefficients	*p*-value	*t-value* (bootstrap)
H1	CEO narcissism → CSI	0.303**	0.007	2.712
H2	CEO power → CSI	0.336*	0.029	2.180
Control	Family ownership → CSI	−0.079	0.574	0.562
Control	Gender diversity → CSI	0.101	0.180	1.341
Control	International diversity → CSI	0.004	0.927	0.092

Table 6. Hypotheses testing

Note(s): *$p < 0.05$; **$p < 0.01$

Source(s): Table by the authors

Mena *et al.* (2016) that consider that CSI degree is related to the harm caused that is best conceptualized in degrees. In that sense, we read the news of our sample and evaluated the harm varying from the maximum of loss of human life, to the loss of nonhuman life or to the minimum, loss of livelihoods in local communities. Our expectation was corroborated by a significant, positive correlation between the degree of CSI and harm ($r = 0.77$, $p < 0.01$), increasing our confidence in the measure's validity.

We repeated the analyses with a new dependent variable. In order to create a new CSI variable with four indicators (three experts and the degree of harm), we first transform each indicator to a scale from zero to one. The scale has a good CA ($\alpha = 0.94$). We then run, through SEM estimations and PLS, the basic model regarding hypothesis 1 and 2 without control variables [21] and our results remain stable providing support for both hypotheses. PLS results provide an adjusted R^2, of 10.4%. CEO narcissism does have a significant effect on the new measure of CSI ($\beta = 0.633$; $p < 0.01$; $f^2 = 0.10$). Thus, we find evidence to support Hypothesis 1. Additionally, CEO power has a significant effect on CSI ($\beta = 0.482$; $p < 0.05$; $f^2 = 0.06$), which confirms Hypothesis 2. We ran SEM estimations and the results were maintained with the new dependent variable; narcissism remains a clearly significant variable ($\beta = 0.156$; $p < 0.05$) and CEO power has only a significance of $p = 0.056$.

Discussion and conclusions

The recent increase in corporate scandals has fostered concern among managers and researchers, about CSI and its antecedents, opening up many new research questions. In this respect, the purpose of this article is to contribute to the literature by studying CSI antecedents revealing the key role managers play in their companies' irresponsible behaviors. This is the reason why some scholars have suggested the need to study specific individual traits of CEOs as CSI antecedents (Grijalva and Harms, 2014), which is theoretically and empirically attractive.

In respect to CSI, we add new evidence to the underdeveloped line of research that links individual level antecedents with CSI behaviors (Grijalva and Harms, 2014; Iborra and Riera, 2023). By focusing on the individual level instead of on institutional variables, we respond to the call made by Ghoshal (2005) that CEOs are not free from moral or ethical responsibility for their actions and, as shown, we have found empirical support for this argument. We argue and provide evidence that internal factors belonging to the characteristics of the upper echelons of the firm are key antecedents of CSI. In other words, CSI is not just a matter of good firms in bad context: CEOs do matter.

Our research extends the upper echelons theory arguing that CEOs play a key role in explaining CSI. Specifically, we contribute to the literature arguing and providing evidence that CEO narcissism and CEO power, may be considered CSI antecedents.

Regarding narcissism, previous empirical studies have provided contradictory evidence in respect to its positive or negative consequences (Chatterjee and Hambrick, 2007; Cragun *et al.*, 2020; Salehi *et al.*, 2022). In contrast to researchers who highlighted the bright side of narcissism, in this study, we contribute to research on CEO narcissism by analyzing its darker side in explaining CSI which, to date, has only scarcely being examined. For example, Almaleki *et al.* (2021) found support for the negative impact of CEO narcissism on the quality of financial statements in a sample of 128 Iran firms from 2012 to 2018. They argue that narcissistic CEOs are likely to deliberately distort information, leading to a lack of disclosure of bad news to stakeholders and manipulating them for achieving support, i.e. causing harm to them. Our study provides support for the idea that narcissistic CEOs ignore the interest of third parties, increasing the likelihood of doing harm. This evidence fits with the findings of O'Reilly *et al.* (2018) for narcissistic CEOs denying the experts' opinion which implies not taking care and be aware of the consequences of the actions. It is also in line with the proposal

of Salehi *et al.* (2022) that highlights as negative dimensions of narcissism their lack of cooperation and low tolerance to criticism. In sum, narcissistic CEOs are individuals who lack empathy and disregard potential concerns increasing the likelihood of doing harm. We provide evidence that this specific trait of CEO narcissism is linked to the degree of CSI. Our evidence is in line with the statement of Cragun *et al.* (2020) that narcissistic CEOs can cause great harm. This calls for future research that examines which factors might amplify or mitigate these outcomes.

In addition, our evidence supports that power in corporations is a key issue to be taken into account when examining CSI. Power centralization of the CEOs implies that they are not subject to the control and monitoring of others. They can act not taking into account the points of view, interests or demands of others. They can act without a counterbalance. According to Pearce and Manz (2011), centralized decision-making is not aligned with the objectives, interests or needs of the rest of the members of the company. Moreover, powerful CEOs may ignore the need for accountability and may increase the chances for corruptive behaviors to occur. As Cragun *et al.* (2020) suggest the effect of CEO narcissism could differ by the context: BoD may communicate to a CEO through diverse means that narcissistic behavior is approved or avoided. Our evidence supports this relationship.

Our study also contributes to the empirical research on CSI. The CSI is a complex issue to study. The absence of empirical studies in this field, except for those made on large public firms or case studies, confirm this difficulty (Iborra and Riera, 2023). Using secondary sources, we develop a new approach to this question. We also provide a way to measure the degree of CSI, and not merely its existence or absence, through a panel of experts that allows us to take into account the diversity of views and perceptions of CSI. Hence, bearing in mind Armstrong's (1977: 1) definition in which he states that "an act is irresponsible if a vast majority of unbiased observers would agree that this is so", we propose a novel method for measuring CSI and evaluating different corporate irresponsible behaviors and their degrees based on the perceptions of an unbiased experts' panel.

Managerial implications

Our research shows that the executives' personality is relevant to explain CSI. Increasing their understanding and awareness of CSI may favor to control and prevent it.

We cannot deny that top managers tend to be narcissistic and they are going to be more in the future. First, because researchers evidence the predominance of narcissistic profiles among CEOs (Cragun *et al.*, 2020); second, because narcissistic individuals tend to become CEOs earlier in their careers (O'Reilly *et al.*, 2018); and, lastly, because the next generations of managers have received a parental education and will live in a social context that will increase their trend to narcissism (Young *et al.*, 2016). So, if narcissism will be there, firms have to look for ways that counterbalance narcissism's dark side.

In this study, we found evidence of the relationship between CEO narcissism and power and CSI. Firms should handle power by setting up diverse and pluralistic structures, through the assessment of TMTs and board compositions. In doing so, collaboration and cooperation would emerge, which may compensate for the effect of narcissistic behaviors.

Finally, this study offers CEOs further guidance on making optimal decisions to prevent CSI. The more narcissistic CEOs are, the greater the need to counterbalance their power to avoid the likelihood of CSI.

Further lines of research and limitations

Our paper fosters the development of new lines of research. We reveal that the role played by CEOs, together with power distribution, have an influence on CSI. However, literature dealing with the upper echelons theory (Finkelstein *et al.*, 2009), suggests that other variables related

to the board composition, as well as TMT diversity, may also have an impact on decision making. As additional future research lines, we propose to carry out further studies regarding CSI antecedents at the individual level. A future line of insight that has provide some light in related areas as CSR is the relationship between CEOs, TMTs and BoD characteristics in explaining CSI (Shafeeq Nimr Al-Maliki *et al.*, 2023). This will provide light on CSI decision-making processes by examining CEOs, TMTs, BoD and their interfaces.

Additional research is also needed to improve knowledge of the role of corporate control and prevention tools to mitigate the likelihood of CSI under narcissistic individuals (Young *et al.*, 2016). This may open future research that carries out a more thorough study on antecedents at diverse levels, since there is still no clear understanding of which variables are antecedents of CSI (Zhao *et al.*, 2014). Multilevel analysis would significantly improve CSI areas, both at the firm level and the individual level (Iborra and Riera, 2023).

Additionally, although family ownership has been studied as a control variable in this work, we stress the importance of focusing on specific family firm characteristics. Family firms are a complex reality, which involves more dimensions than merely considering the percentage of shareholder's equity owned by family members.

This study has some methodological limitations. Specifically, the main limitation of our work comes from the sample size. We obtained a sample of only 84 companies due to limited information on narcissism in SMEs. Different reasons may explain it. On the one hand, Spain is the 11th country with more LinkedIn connections (more than 13 million people) but people with ages between 25 and 34 years old, represent more than a half of the accounts in this platform (Statista, 2021) and are unlikely CEOs at these ages. Only 191,416 registered company pages from more than three million of Spanish companies are at LinkedIn decreasing the likelihood of representation. In addition, managers may have removed their LinkedIn profile in order to eliminate any personal information after CSI is known.

Another limitation comes from the sample selection. We focus on understanding the degree of CSI; so, we took into consideration only companies that caused different types of harm to social, economic or/and environmental dimensions and do it in different degrees. We base this option in our conceptualization of CSI as a standalone construct [22]. Future research may devise a more thorough approach improving the understanding of the role of CEOs narcissism and power considering both responsible companies and irresponsible companies in their sample.

Notes

1. For recent reviews see Iborra and Riera (2023) and Mendiratta *et al.* (2023).
2. For recent reviews focused on multinationals behaviors see Cuervo-Cazurra *et al.* (2021) and Nieri and Giuliani, (2018).
3. For example, Rovelli *et al.* (2023) demonstrate that CEO narcissism as a personality trait offers family firm some important business advantages related to innovation.
4. This idea is in line with Salehi *et al.* (2021) description of the "dark side" of managers when capable managers may misuse their authority, which leads to manipulation.
5. Also, specific consequences call for attention as Feng *et al.* (2022) evidence for transaction costs.
6. Clark *et al.* (2022) argue that defining CSR and CSI as opposite constructs produces a lack of clarity between responsible and irresponsible acts.
7. Intentionality is defined in a broad sense including that the company does it knowing the consequences of the act, or being negligent or reckless (Godfrey, 2005; Clark *et al.*, 2022).
8. However, when breaking down the studies by the different measures used for narcissism, only the ones that used indexes remain significant.

9. A sample of Spanish companies has been chosen due to the importance to delimit the institutional context of the study. Each country has a unique index of corruption (Transparency International, 2022) and the national context of each country clarifies the situation of corruption, without the distortion of other variables.
10. This period of time has been chosen due to the correspondence of an economic boom period in Spain (from 2005 to 2007) and a period of deep economic crisis (2008–2012) periods, where there was evidence of emergence of corporate irresponsible behaviors.
11. Spanish terms were used for the search.
12. This is the Spanish antitrust law similar to the Federal Trade Commission act that bans unfair methods of competition and unfair or deceptive acts.
13. The percentage of large companies in Spain is much lower (0.3% of the total number of companies) but media news focus more on well-known large companies. The percentage of industries is similar to the one in Spain (INE, 2018).
14. According to Utkin (2006), advice from experts is useful when information is limited, as occurs in this work.
15. Recently, new CSI measures have been introduced—e.g. Wang and Li (2019)—which mainly focus on reputation and industries for measuring CSI behaviors and which are related to corporate size.
16. This database focuses on large companies which limits its usefulness for other contexts as SMEs (Iborra and Riera, 2023).
17. Our definition does not consider that CSI is the opposite of CSR. As Clark *et al.* (2022) state, CSI is not conceptualized as simply the opposite of CSR, but it is a broader construct that relies on specific and idiosyncratic elements. Being one of them, harm, which occurs in degrees from the loss of human life, to the loss of nonhuman life or to the loss of livelihoods in local communities (Mena *et al.*, 2016; Clark *et al.*, 2022).
18. The existence of the BoD and its characteristics has been related to the involvement in CSR through their role in informing and monitoring CEO activity (Shafeeq Nimr Al-Maliki *et al.*, 2023).
19. The ownership characteristics have been linked with the potential conflicts between CEO and shareholders and to the level and growth of CSR (Salehi and Alkhyyoon, 2022).
20. Only one indicator of CEO narcissism has an individual standardized loading of 0.674; The mean of the individual standardized loadings is 0.774 higher than the threshold of 0.7 (Chin, 1998).
21. The main reason for using PLS was the small size of our sample.
22. Clark *et al.* (2022, p. 21) clearly illustrate this point when they argue: "our argument parallels conceptual research on satisfaction and dissatisfaction where the opposite of satisfaction, is no satisfaction and the opposite of dissatisfaction, no dissatisfaction (Herzberg, 1968). We argue, then, that the opposite of CSI is not CSR but 'no CSI.'"

References

Aabo, T. and Eriksen, N.B. (2018), "Corporate risk and the humpback of CEO narcissism", *Review of Behavioral Finance*, Vol. 10 No. 3, pp. 252-273.

Abbasi, M.A. and Amran, A. (2023), "Linking corporate social irresponsibility with workplace deviant behaviour: mediated by moral outrage", *Journal of Global Responsibility*, Vol. 14 No. 2, pp. 200-221.

Almaleki, M., Salehi, M. and Moradi, M. (2021), "The relationship between narcissism, managerial overconfidence and comparability of financial statements of listed companies", *Journal of Facilites Management*, Vol. 19 No. 5, pp. 681-700.

Andreoli, N. and Lefkowitz, J. (2009), "Individual and organizational antecedents of misconduct in organizations", *Journal of Business Ethics*, Vol. 85 No. 3, pp. 309-332.

Anninos, L.N. (2018), "Narcissistic business leaders as heralds of the self-proclaimed excellence", *International Journal of Quality and Service Sciences*, Vol. 10 No. 1, pp. 49-60.

Antonetti, P. (2020), "More than just a feeling: a research agenda for the study of consumer emotions following Corporate social irresponsibility (CSI)", *Australasian Marketing Journal*, Vol. 28 No. 2, pp. 67-70.

Armstrong, J.S. (1977), "Social irresponsibility in management", *Journal of Business Research*, Vol. 5 No. 3, pp. 185-213.

Ashforth, B.E. and Anand, V. (2003), "The normalization of corruption in organizations", *Research in Organizational Behavior*, Vol. 25, pp. 1-52.

Ayuso, S. and Argandoña, A. (2007), "Responsible corporate governance: towards a stakeholder board of directors?", *SSRN Electronic Journal*, Vol. 6 No. 4, doi: 10.2139/ssrn.1349090.

Bagozzi, R. and Yi, Y. (1988), "On the evaluation of structural equation models", *Journal of the Academy of Marketing Sciences*, Vol. 16, pp. 74-94.

Berrone, P., Cruz, C., Gómez-Mejía, L. and Larraza-Kintana, M. (2010), "Socioemotional wealth and corporate responses to institutional pressures: do family-controlled firms pollute less?", *Administrative Science Quarterly*, Vol. 55, pp. 82-113.

Bogart, L.M., Benotsch, E.G. and Pavlovic, J.D.P. (2004), "Feeling superior but threatened: the relation of narcissism to social comparison", *Basic and Applied Social Psychology*, Vol. 26 No. 1, pp. 35-44.

Boudier, F. and Bensebaa, F. (2011), "Hazardous waste management and corporate social responsibility: illegal trade of electrical and electronic waste", *Business and Society Review*, Vol. 116 No. 1, pp. 29-53.

Brammer, S., Millington, A. and Rayton, B. (2007), "The contribution of corporation social responsibility to organizational commitment", *International Journal of Human Resource Management*, Vol. 18 No. 10, pp. 1701-1719.

Buss, D.M. and Chiodo, L.M. (1991), "Narcissistic acts in everyday life", *Journal of Personality*, Vol. 59 No. 2, pp. 179-215.

Campbell, W.K. and Foster, J.D. (2007), "The narcissistic self: background, an extended agency model and ongoing controversies", *The Self*, Psychology Press, pp. 115-138.

Campbell, W.K. and Siedor, L. (2016), "Narcissism and dishonesty: the SAC model", in Van Prooijen, J.-W. and Van Lange, P.A.M. (Eds), *Cheating, Corruption, and Concealment*, pp. 151-165.

Campbell, W.K., Goodie, A.S. and Foster, J.D. (2004), "Narcissism, confidence, and risk attitude", *Journal of Behavioral Decision Making*, Vol. 17 No. 4, pp. 297-311.

Campbell, W.K., Hoffman, B.J., Campbell, S.M. and Marchisio, G. (2011), "Narcissism in organizational contexts", *Human Resource Management Review*, Vol. 21 No. 4, pp. 268-284.

Carroll, A.B. (1979), "A three-dimensional conceptual model of corporate performance", *Academy of Management Review*, Vol. 4 No. 4, pp. 497-505.

Chatterjee, A. and Hambrick, D.C. (2007), "It's all about me: narcissistic chief executive officers and their effects on company strategy and performance", *Administrative Science Quarterly*, Vol. 52 No. 3, pp. 351-386.

Chatterjee, A. and Pollock, T.G. (2017), "Master of puppets: how narcissistic CEOs construct their professional worlds", *Academy of Management Review*, Vol. 42 No. 4, pp. 703-725.

Chen, Y., Ferris, D.L., Kwan, H.K., Yan, M., Zhou, M. and Hong, Y. (2013), "Self-love's lost labor: a self-enhancement model of workplace incivility", *Academy of Management Journal*, Vol. 56 No. 4, pp. 1199-1219.

Chin, W.W. (1998), "The partial least squares approach to structural equation modeling", *Modern Methods for Business Research*, Vol. 295 No. 2, pp. 295-336.

Clark, C.E., Riera, M. and Iborra, M. (2022), "Toward a theoretical framework of corporate social irresponsibility: clarifying the gray zones between responsibility and irresponsibility", *Business and Society*, Vol. 61 No. 6, pp. 1473-1511.

Cragun, O.R., Olsen, K.J. and Wright, P.M. (2020), "Making CEO narcissism research great: a review and meta-analysis of CEO narcissism", *Journal of Management*, Vol. 46 No. 6, pp. 908-936.

Cuervo-Cazurra, A., Dieleman, M., Hirsch, P., Rodrigues, S.B. and Zyglidopoulos, S. (2021), "Multinationals' misbehavior", *Journal of World Business*, Vol. 56 No. 5, 101244.

de Vries, M.K. (2004), "Organizations on the couch: a clinical perspective on organizational dynamics", *European Management Journal*, Vol. 22 No. 2, pp. 183-200.

Deutschman, A. (2005), "Is your boss a psychopath", *Fast Company*, Vol. 96 No. 7, pp. 44-52.

Ellis, H. (1898), "Auto-erotism: a psychological study", *The Alienist and Neurologist*, Vol. 19, pp. 260-299.

Emmons, R.A. (1987), "Narcissism: theory and measurement", *Journal of Personality and Social Psychology*, Vol. 52 No. 1, p. 11.

Faul, F., Erdfelder, E., Buchner, A. and Lang, A.G. (2009), "Statistical power analyses using G*power 3.1: tests for correlation and regression analyses", *Behavior Research Methods*, Vol. 41, pp. 1149-1160.

Feng, T., Yang, F., Tan, B. and Wu, J. (2022), "Corporate social irresponsibility punishments from stakeholders—evidence from China", *Sustainability*, Vol. 14 No. 8, p. 4678.

Finkelstein, S., Hambrick, D.C. and Cannella, A.A. (2009), *Strategic Leadership*, Oxford University Press, Oxford.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement Error", *Journal of Marketing Research*, Vol. 18, pp. 39-50.

Freud, S. (1957), "The history of the psychoanalytic movement", *The Standard Edition of the Complete Works of Sigmund Freud*, Hogarth Press, London, pp. 617-633.

Garriga, E. and Melé, D. (2004), "Corporate social responsibility theories: mapping the territory", *Journal of Business Ethics*, Vol. 53 Nos 1-2, pp. 51-71.

Geisser, S. (1974), "A predictive approach to the random effects model", *Biometrika*, Vol. 61, pp. 101-107.

Ghoshal, S. (2005), "Bad management theories are destroying good management practices", *Academy of Management Learning and Education*, Vol. 4 No. 1, pp. 75-91.

Gómez-Mejía, L., Cruz, C. and Imperatore, C. (2014), "Financial Reporting and the protection of socioemotional wealth in family-controlled firms", *European Accounting Review*, Vol. 23 No. 3, pp. 387-402.

Godfrey, P.C. (2005), "The relationship between corporate philanthropy and shareholder wealth: a risk management perspective", *Academy of Management Review*, Vol. 30 No. 4, pp. 777-798.

Grijalva, E. and Harms, P.D. (2014), "Narcissism: an integrative synthesis and dominance complementarity model", *Academy of Management Perspectives*, Vol. 28 No. 2, pp. 108-127.

Hair, J.F., Sarstedt, M., Ringle, C.M. and Mena, J.A. (2012), "An assessment of the use of partial least squares structural equation modeling in marketing research", *Journal of the Academy of Marketing Science*, Vol. 40 No. 3, pp. 414-433.

Hambrick, D.C. and Mason, P.A. (1984), "Upper echelons: the organization as a reflection of its top managers", *Academy of Management Review*, Vol. 9 No. 2, pp. 193-206.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115-135.

Herzberg, F. (1968), "One more time: how do you motivate employees", *Harvard Business Review*, Vol. 46 No. 1, pp. 53-62.

Iborra, M. and Riera, M. (2023), "Corporate social irresponsibility: what we know and what we need to know", *Corporate Social Responsibility and Environmental Management*, Vol. 30 No. 1, pp. 1421-1439, doi: 10.1002/csr.2428.

INE (2018), available at: https://www.ine.es/index.htm

Judge, T.A., LePine, J.A. and Rich, B.L. (2006), "Loving yourself abundantly: relationship of the narcissistic personality to self-and other perceptions of workplace deviance, leadership and task and contextual performance", *Journal of Applied Psychology*, Vol. 91 No. 4, p. 762.

Keig, D.L., Brouthers, L.E. and Marshall, V.B. (2015), "Formal and informal corruption environments and multinational enterprise social irresponsibility", *Journal of Management Studies*, Vol. 52 No. 1, pp. 89-116.

Kemp, D. and Owen, J.R. (2022), "Corporate social irresponsibility, hostile organisations and global resource extraction", *Corporate Social Responsibility and Environmental Management*, Vol. 29 No. 5, pp. 1816-1824.

Kim, B., Lee, S. and Kang, K.H. (2018), "The moderating role of CEO narcissism on the relationship between uncertainty avoidance and CSR", *Tourism Management*, Vol. 67, pp. 203-213.

Laguir, I., Laguir, L. and Elbaz, J. (2016), "Are family small-and medium-sized enterprises more socially responsible than nonfamily small-and medium-sized enterprises?", *Corporate Social Responsibility and Environmental Management*, Vol. 23 No. 6, pp. 386-398.

Lee, C.-Y., Wu, H.-L. and Lee, C.-J. (2018), "Does CEO career horizon lead to corporate misconduct? Evidence of Taiwanese semiconductor firms", *NTU Management Review*, Vol. 28 No. 3, pp. 145-176.

Lister, E.D. (2004), "The productive narcissist: the promise and peril of visionary leadership", *Psychiatric Services*, Vol. 55 No. 9, p. 1070.

Maccoby, M. (2000), "Narcissistic leaders: the incredible pros, the inevitable cons", *Harvard Business Review*, Vol. 78 No. 1, pp. 68-78.

Matten, D. and Moon, J. (2005), "Pan-European approach: a conceptual framework for understanding CSR", in Habisch, A., Wegner, M., Schmidpeter, R. and Corporate, J.J. (Eds), *Social Responsibility across Europe*, Springer, Berlin, pp. 335-356.

Matten, D. and Moon, J. (2008), "'Implicit' and 'Explicit' CSR: a conceptual framework for a comparative understanding of corporate social responsibility", *The Academy of Management Review*, Vol. 33, p. 3.

Mena, S., Rintamäki, J., Fleming, P. and Spicer, A. (2016), "On the forgetting of corporate irresponsibility", *Academy of Management Review*, Vol. 41, pp. 720-738.

Mendiratta, A., Singh, S., Yadav, S. and Mahajan, A. (2023), "Bibliometric and topic modeling analysis of corporate social irresponsibility", *Global Journal of Flexible Systems Management*, Vol. 24, pp. 319-339.

Myung, J.K., Choi, Y.H. and Kim, J.D. (2017), "Effects of CEOs' negative traits on corporate social responsibility", *Sustainability*, Vol. 9 No. 4, p. 543.

Nevicka, B., Ten Velden, F.S., De Hoogh, A.H. and Van Vianen, A.E. (2011), "Reality at odds with perceptions: narcissistic leaders and group performance", *Psychological Science*, Vol. 22 No. 10, pp. 1259-1264.

O'Reilly, C., Chatman, J. and Doerr, B. (2018), "When 'me' trumps 'we': narcissistic leaders and the cultures they create", *Academy of Management Proceedings*, Vol. 11515, doi: 10.5465/AMBPP.2018.11515abstract.

Nieri, F. and Giuliani, E. (2018), "International business and corporate wrongdoing: a review and research agenda", *Contemporary Issues in International Business*, pp. 35-53.

Oesterle, M., Elosge, C. and Elosge, L. (2016), "Me, myself and I: the role of CEO narcissism in internationalization decisions", *International Business Review*, Vol. 25 No. 5, pp. 1114-1123.

Oh, W.Y., Chang, Y.K. and Jung, R. (2018), "Experience-based human capital or fixed paradigm problem? CEO tenure, contextual influences, and corporate social (ir) responsibility", *Journal of Business Research*, Vol. 90, pp. 325-333.

Pearce, C.L. (1997), "The determinants of change management team (CMT) effectiveness: a longitudinal investigation", (Unpublished doctoral dissertation), University of Maryland, College Park.

Pearce, C. and Manz, C. (2011), "Leadership centrality and corporate social ir-responsibility (CSIR): the potential ameliorating effects of self and shared leadership on CSIR", *Journal of Business Ethics*, Vol. 102 No. 4, pp. 563-579.

Pearce, C., Manz, C. and Sims, H. (2008), "The roles of vertical and shared leadership in the enactment of executive corruption: implications for research and practice", *The Leadership Quarterly*, Vol. 19 No. 3, pp. 353-359.

Petrenko, O.V., Aime, F., Ridge, J. and Hill, A. (2016), "Corporate social responsibility or CEO narcissism? CSR motivations and organizational performance", *Strategic Management Journal*, Vol. 37 No. 2, pp. 262-279.

Pitcher, P. and Smith, A. (2001), "Top management team heterogeneity: personality, power, and proxies", *Organization Science*, Vol. 12 No. 1, pp. 1-18.

Raskin, R.N. and Hall, C.S. (1979), "A narcissistic personality inventory", *Psychological Reports*, Vol. 45 No. 2, p. 590.

Riera, M. and Iborra, M. (2017), "Corporate social irresponsibility: review and conceptual boundaries", *European Journal of Management and Business Economics*, Vol. 26 No. 2, pp. 146-162.

Rijsenbilt, A. and Commandeur, H. (2013), "Narcissus enters the courtroom", *Journal of Business Ethics*, Vol. 117 No. 2, pp. 413-429.

Ringle, C.M., Wende, S. and Becker, J.M. (2022), "SmartPLS 4", SmartPLS GmbH, Oststeinbek, available at: http://www.smartpls.com

Rovelli, P. and Curnis, C. (2021), "The perks of narcissism: behaving like a star speeds up career advancement to the CEO position", *The Leadership Quarterly*, Vol. 32 No. 3, 101489.

Rovelli, P., De Massis, A. and Gomez-Mejia, L.R. (2023), "Are narcissistic CEOs good or bad for family firm innovation?", *Human Relations*, Vol. 76 No. 5, pp. 776-806.

Salehi, M. and Alkhyyoon, H. (2022), "The relationship between managerial entrenchment, social responsibility, and firm's risk-taking and shareholders' activity", *Social Responsibility Journal*, Vol. 18 No. 5, pp. 1035-1049.

Salehi, M., Naeini, A. and Rouhi, S. (2020), "The relationship between manager' narcissism and overconfidence on corporate risk-taking", *The TQM Journal*, Vol. 33 No. 6, pp. 1123-1142.

Salehi, M., Dashtbayaz, M.L. and Hosseinkamal, M. (2021), "The relationship between supervision quality, CEO's ability and authority with firm performance", *Journal of Facilities Management*, Vol. 19 No. 2, pp. 50-173.

Salehi, M., Rouhi, S., Usefi Moghadam, M. and Faramarzi, F. (2022), "Managers' and auditors' narcissism on the management team's stability and relative corporate performance", *International Journal of Productivity and Performance Management*, Vol. 71 No. 4, pp. 1490-1514.

Seifzadeh, M., Salehi, M., Abedini, B. and Ranjbar, M.H. (2021), "The relationship between management characteristics and financial statement readability", *EuroMed Journal of Business*, Vol. 16 No. 1, pp. 108-126.

Shafeeq Nimr Al-Maliki, H., Salehi, M. and Kardan, B. (2023), "The relationship between board characteristics and social responsibility with firm innovation", *European Journal of Management and Business Economics*, Vol. 32 No. 1, pp. 113-129.

Skjong, R. and Wentworth, B.H. (2001), "Expert judgment and risk perception", *Paper presented at the The Eleventh International Offshore and Polar Engineering Conference*.

Statista. (2021), available at: https://www.statista.com/statistics/273505/global-linkedin-age-group/

Stone, M. (1974), "Cross-validatory choice and assessment of statistical predictions", *Journal of the Royal Statistical Society*, Vol. 36 No. 1, pp. 111-147.

Strike, V.M., Gao, J. and Bansal, P. (2006), "Being good while being bad: social responsibility and the international diversification of US firms", *Journal of International Business Studies*, Vol. 37 No. 6, pp. 850-862.

Sun, W. and Ding, Z. (2021), "Is doing bad always punished? A moderated longitudinal analysis on corporate social irresponsibility and firm value", *Business and Society*, Vol. 60 No. 7, pp. 1811-1848.

Surroca, J., Tribó, J.A. and Zahra, S.A. (2013), "Stakeholder pressure on MNEs and the transfer of socially irresponsible practices to subsidiaries", *Academy of Management Journal*, Vol. 56 No. 2, pp. 549-572.

Tajfel, H. (2010), *Social Identity and Intergroup Relations*, Cambridge University Press, New York.

Tang, Y., Mack, D.Z. and Chen, G. (2018), "The differential effects of CEO narcissism and hubris on corporate social responsibility", *Strategic Management Journal*, Vol. 39 No. 5, pp. 1370-1387.

Transparency International. (2022), available at: https://www.transparency.org/en/cpi/2022

Utkin, L.V. (2006), "A method for processing the unreliable expert judgments about parameters of probability distributions", *European Journal of Operational Research*, Vol. 175 No. 1, pp. 385-398.

Valor, C., Antonetti, P. and Zasuwa, G. (2022), "Corporate social irresponsibility and consumer punishment: a systematic review and research agenda", *Journal of Business Research*, Vol. 144, pp. 1218-1233.

Waldman, D.A. and Siegel, D. (2008), "Defining the socially responsible leader", *The Leadership Quarterly*, Vol. 19 No. 1, pp. 117-131.

Wales, W.J., Patel, P.C. and Lumpkin, G.T. (2013), "In pursuit of greatness: CEO narcissism, entrepreneurial orientation, and firm performance variance", *Journal of Management Studies*, Vol. 50 No. 6, pp. 1041-1069.

Wang, S.L. and Li, D. (2019), "Responding to public disclosure of corporate social irresponsibility in host countries: information control and ownership control", *Journal of International Business Studies*, Vol. 50 No. 8, pp. 1283-1309.

Wong, E.M., Ormiston, M.E. and Tetlock, P.E. (2011), "The effects of top management team integrative complexity and decentralized decision making on corporate social performance", *Academy of Management Journal*, Vol. 54 No. 6, pp. 1207-1228.

Young, S.M., Du, F., Dworkis, K.K. and Olsen, K.J. (2016), "It's all about all of us: the rise of narcissism and its implications for management control system research", *Journal of Management Accounting Research*, Vol. 28 No. 1, pp. 39-55.

Zhao, M., Tan, J., Ho Park, S. (2014), "From voids to sophistication: institutional environment and MNC CSR crisis in emerging markets", *Journal of Business Ethics*, Vol. 122 No. 4, pp. 655-674.

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The impact of economic policy uncertainty on stock types while considering the economic cycle. A quantile regression approach

Received 6 December 2022
Revised 26 May 2023
17 July 2023
27 July 2023
9 August 2023
Accepted 11 August 2023

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Abstract

Purpose – This study aims to analyse the effects of Economic Policy Uncertainty (EPU) on the return of growth/value and small/large-cap stocks during expansionary and recessionary periods across a conditional distribution.

Design/methodology/approach – The authors selected a sample covering the period between 01/1995–05/2021. Quantile regressions were applied to the EPU and Russell indices. Business cycles were established following the NBER.

Findings – The results show that EPU has a negative effect on stocks with the intensity of the effect depending on the stock's profile. Small-cap and growth stocks were found to be most sensitive to EPU, especially during recessions. The negative effect is moderated by the economic cycle but is progressively diluted at the lower tail of the stock return distribution.

Practical implications – The findings shed more light on investment strategies for growth/value investors that pursue opportunities arising from a changing economic cycle.

Originality/value – This study makes the following contributions: (1) explores the impact of EPU on the return of different stocks across a conditional distribution, and (2) provides evidence on how the economic cycle influences EPU impact on growth/value stocks and small/large stocks.

Keywords Economic policy uncertainty, Stock market returns, Limited arbitrage, Economic cycles, Behavioural finance

Paper type Research paper

Introduction

Following Keynes' (1937) suggestion that uncertainty is a fundamental element in the economy, the literature has focused particularly on the study of Economic Policy Uncertainty (EPU) and its consequences. This interest increased with the uncertainties derived from the global financial crisis (2007–2009) that contributed to a sharp economic decline, as well as to its subsequent slow recovery (International Monetary Fund, 2013; Baker *et al.*, 2016).

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement: Data available on request from the authors

European Journal of Management and Business Economics
Vol. 34 No. 1, 2025
pp. 88-102
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-12-2022-0365

Changes in existing economic policies, or even the speed of changes agreed in these policies, can influence investors, generating a sentiment of insecurity in their expectations or judgements about the value of assets (Alcázar-Blanco *et al.*, 2021). The most recent literature confirms that EPU influences the asset pricing of many markets, including stocks (Antonakakis *et al.*, 2013; Arouri *et al.*, 2016), bonds (Ioannidis and Ka, 2021; Pham and Nguyen, 2022) and cryptocurrencies (Cheng and Yen, 2020; Paule-Vianez *et al.*, 2020), among others.

The impact of EPU on stock market returns has been well researched, with results showing strong evidence of a negative influence (Baker *et al.*, 2016; Arouri *et al.*, 2016). Increased EPU amplifies behavioural biases, with mixed results being found on the impact of EPU on individual stocks (Hu *et al.*, 2018; Luo and Zhang, 2020). Analysing investor sentiment, some authors show a stronger impact for small-cap and growth stocks (Lakonishok *et al.*, 1994; Baker and Wurgler, 2006; Waggle and Agrrawal, 2015; Wu *et al.*, 2014; Smales, 2017), while others defend the view that the impact is stronger for value stocks (Kumar and Lee, 2006; Bathia and Bredin, 2013). Under uncertainty, Hu *et al.* (2018) reveal that small and growth stocks in China's A-share market are more sensitive to US EPU shocks.

The economic cycle plays a key role in the impact of EPU on investor confidence levels (Ahmad and Sharma, 2018; Adjei *et al.*, 2022). Policymakers experience more pressure to stimulate the economy during economic downturns, and investors are more sensitive to their doubts (Adjei and Adjei, 2017). This is further evidenced in the influence of EPU in value premium (Bretschger and Lechthaler, 2018; Kirby, 2019).

However, EPU impact is not the same in the lower and the upper quantiles of stock returns (Kannadhasan and Das, 2020), nor in the nonlinear predictability US equity premium models (Bekiros *et al.*, 2016). For example, Raza *et al.* (2018) showed that the relationship between equity premium and EPU is especially negative in the extreme low and high tails.

Considering that the impact of EPU on stock market returns does not have to be uniform and given the precedents of the amplification of the behavioural biases under uncertainty, this research goes deeper into considering relationships that prior literature had researched independently. The objectives of this study are therefore: (1) to explore whether the EPU impact on different types of stocks differs depending on the most or least profitable stocks, and (2) to examine how the economic cycle moderates the influence of EPU on stock return considering the different types of stocks.

Advancing on the approaches undertaken in previous literature, we propose the use of quantile regression to evaluate EPU impact, as this methodology offers a more comprehensive dependence structure for the analysis of stock returns under diverse market conditions (Bekiros *et al.*, 2016; Kannadhasan and Das, 2020; Jiang *et al.*, 2022). Linear models based on the conditional-mean are insufficient to explain the entire conditional distribution of the value premium (Bekiros and Gupta, 2015). We apply Ordinary Least Squares (OLS) with heteroskedasticity correction to analyse the robustness of the results.

This study makes a comprehensive contribution to the EPU literature related to value/growth and small/large cap stock returns, exploring the role the economic cycle plays in this impact and the effect under different conditions of the stock market. This new evidence offers more insight for investments strategies for growth/value investors that pursue opportunities arising from the changing economic cycle.

The paper is structured as follows: Section 2 addresses the theoretical framework involved in the study, and Section 3 explains the data and variables used in the study. Section 4 explains the methodology, and in Section 5, the results are presented and discussed. Finally, Section 6 shows the conclusions.

Theoretical framework

Information uncertainty is behind several findings that contradict the theory of equilibrium in financial markets (Jiang *et al.*, 2005). Several authors have documented how uncertainty related to social, political or economic conditions has a considerable influence on investor sentiment (Beugelsdijk and Frijns, 2010; Kumar *et al.*, 2012). Brown and Cliff (2005) found that investor sentiment is due to persistent and uninformed demand shocks, which leads to a poor valuation of prices in the presence of limits to arbitrage.

In this paper, we use EPU, understanding it as the "non-zero probability of changes in existing economic policies" (Baker *et al.*, 2016). Uncertainty can increase when those responsible for economic policies fail to reach timely agreements or change policies frequently (Li *et al.*, 2015). Even media speculations can influence uncertainty (Adjei and Adjei, 2017). Since the inception of EPU, there is considerable evidence of its negative impact on the stock returns using different methodologies and stock markets (Antonakakis *et al.*, 2013; Kang and Ratti, 2013; between others).

Studies focused on the impact of investor sentiment have shown that stocks are affected by behavioural biases, especially in stocks that are more subjective to value or are faced by limits to arbitrage, such as small-cap stocks (Smales, 2017). In this sense, behavioural indicators such sentiment have a great explanatory power (Lemmon and Portniaguina, 2006) or confidence index that has a high predictive capacity for small-cap returns (Kumar and Lee, 2006). In addition, growth stocks overprice with investor overreactions (Lakonishok *et al.*, 1994), especially with bullish sentiment (Waggle and Agrrawal, 2015), making them more prone to bubbles (Baker and Wurgler, 2006). Extreme pessimism also affects growth stocks much more than value stocks (Wu *et al.*, 2014). Therefore, growth stocks are more sensitive to changes in investor confidence.

Though it is confirmed that the impact of investor sentiment is especially negative on small and growth stocks, the effect is no so clear under uncertainty. Studies first showed small-cap and value stocks as the most affected negatively by EPU (Aboura and Arisoy, 2017) and most predictable in bearish markets (Chen *et al.*, 2018). In contrast, recent research shows small-cap and growth stocks to be most affected by EPU (Hu *et al.*, 2018; Luo and Zhang, 2020). These studies highlight the need for more research on the differential factor behind these mixed results, leading us to the following hypothesis:

H1. EPU has a greater negative impact on growth and small-cap stocks.

The relationship between stock returns and EPU is not linear, being stronger and more persistent during periods of extreme volatility (Arouri *et al.*, 2016). The quantile regression methodology allows us to show different asymmetric effects. This approach significantly enhances out-of-sample stock return predictability, especially when the market is neutral (Bekiros *et al.*, 2016). Raza *et al.* (2018) demonstrate that the relationship between equity premium and EPU is especially negative in the extreme low and high tails. Given the prior literature, we test more evidence of the nonlinear relationship between uncertainty and individual stock returns, presenting the following hypothesis:

H2. EPU has a greater impact on the returns of stocks that are at the extremes of the distribution.

The economic cycle is of great importance in the financial markets as an element of systematic risk influencing stock returns (Fama and French, 1989). Generally, there are more economic policy adjustments during periods of recession, and investors respond more to these changes. When the economy contracts, investors expect governmental bodies to take greater measures than during periods of expansion. The speed at which policies are implemented also influences investment risk perception (Pastor and Veronesi, 2013). Thus, there is a high correlation between EPU and the economic cycle (Baker *et al.*, 2016; Adjei and Adjei, 2017).

Evidence shows that a stock's profile is an important element for determining the impact of the economic cycle on stock returns. In regard to value and growth stocks, Fama and French (1992) led a broad literature showing how the value premium is statistically associated with macroeconomic fundamentals (Kelly, 2003; Aretz *et al.*, 2010; among others). More recent literature reassesses that the value premium is related to current and expected economic growth (Lee and Kim, 2017; Bretschger and Lechthaler, 2018), expected business conditions (Kirby, 2019) and future growth consumption (Roh *et al.*, 2019). The role of investor sentiment is more significant in the period preceding the subprime crisis and during the crisis, outperforming value stocks compared with growth stocks (Neves *et al.*, 2021). This evidence could explain how policy makers' intervention in times of recession, while trying to prevent a depression, makes small-growth stocks outperform small-value stocks (Bianchi, 2020).

The size premium is also demonstrated by an extensive literature (Crain, 2011) revealing that small-caps on average outperform large-caps over time, especially during expansions (Kim and Burnie, 2002) and after an economic trough (Switzer, 2010). This effect reflects the firm's exposure to fundamental variables, but Van Dijk (2011) also indicated the non-rationality of valuation models.

Since investor sentiment contributes to size premium (Qadan and Aharon, 2019; Song, 2023), EPU impact is especially negative for small-cap stocks (Killins *et al.*, 2022), and given that size premium is related to the uncertainty with macroeconomic production and aggregate consumption (Scheurle and Spremann, 2010), we test the following hypothesis:

H3. EPU has a greater negative impact on stock returns in times of recession, especially for growth and small-cap stocks.

On the other hand, as noted by Bekiros *et al.* (2016), business cycle fluctuations can cause different EPU impacts on stock returns across quantiles. This may be because this uncertainty could implicitly incorporate information for some parts of the return distribution. This issue has been investigated for the return of momentum strategies but not for stocks in general or the different stock types. Paule-Vianez *et al.* (2021) found that the momentum effect is reduced in the presence of increases in EPU, especially in times of recession and in the lower quantiles of the distribution. However, in periods of expansion, EPU has a positive impact on the upper quantiles. Considering how investor sentiment impacts stock returns, Baker and Wurgler (2006) show how the moderating effect of the business cycle gradually loses its effect as the stock market becomes more bearish. Considering the above, one would expect EPU to have a greater negative impact on lowest stock returns in times of recession. In contrast, EPU impact should be smaller in times of expansion and for the best profitable stocks. Therefore, the last hypothesis we propose to test in this study is:

H4. The economic cycle moderates the influence of EPU on the best profitable stocks.

Data

In this study, we selected a sample covering the period from January 1995 to May 2021 with monthly data.

As a reference of EPU, we selected the US Monthly EPU index of Baker *et al.* (2016) (see http://www.policyuncertainty.com/). This index is based on the frequency with which articles in newspapers refer to words such as "economy" or "economic", "uncertain" or "uncertainty", "deficit", "Federal Reserve", "legislation" and "regulation".

To study the effect of uncertainty on investment returns of value and growth stocks of higher and lower capitalisation, we selected the following indices: Russell 1,000 Value, Russell 1,000 Growth, Russell 2,000 Value and Russell 2,000 Growth. Russell 1,000 Value represents large-cap value stocks, Russell 1,000 Growth represents large-cap growth stocks, Russell

2,000 Value represents small-cap value stocks and Russell 2,000 Growth represents small-cap growth stocks.

Following the proposed objectives, we also distinguish the impact of EPU on stock returns between periods of recession and expansion (Table 1).

Economic variables associated with stock markets and political uncertainty were included as control variables. The variables selected include US inflation (Arouri *et al.*, 2016; Chen *et al.*, 2018), the Industrial Production Index (Arouri *et al.*, 2016; Chen *et al.*, 2018), the term spread between the yield to maturity of a 10-year Treasury note and the 3-month Treasury bill (Brogaard and Detzel, 2015; Adjei and Adjei, 2017), the default spread between yields of BAA-rated bonds and AAA-rated bonds (Brogaard and Detzel, 2015; Arouri *et al.*, 2016; Adjei and Adjei, 2017) and the US gross domestic product index (GDP) (Kurov and Stan, 2018).

Table 2 shows the target study variables, their definition and the sources from which they were extracted.

Methodology

To test the proposed hypotheses, we use quantile regression. This is an extensive form based on traditional regression and can broadly depict a conditional distribution (Lee and Chen, 2021). We use quantile regression to evaluate EPU impact, as this approach offers a more comprehensive dependence structure to the analysis of stock returns under diverse market conditions (Bekiros *et al.*, 2016; Kannadhasan and Das, 2020; Jiang *et al.*, 2022). Additionally,

Table 1.
Periods of recession and expansion in the sample

Period	Economic cycle
January 1995 to March 2001	Expansion
April 2001 to November 2001	Recession
December 2001 to December 2007	Expansion
January 2008 to June 2009	Recession
July 2009 to February 2020	Expansion
March 2020 to April 2020	Recession
May 2020 to May 2021	Expansion

Source(s): National Bureau of Economic Research (NBER)

Table 2.
Description of the target study variables

Variable	Definition	Source
R_{Large_Value}	Return of Russell 1000 Value index	Datastream database
$R_{Large-Growth}$	Return of Russell 1000 Growth index	
$R_{Small-Value}$	Return of Russell 2000 Value index	
$R_{Small-Growth}$	Return of Russell 2000 Growth index	
EPU	Variation rate of US Economic Policy Uncertainty index	Baker *et al.* (2016)
Cycle	Recession (1) or Expansion (2)	National Bureau of Economic Research (NBER)
Default_ spread	Default spread between yields of BAAs-rated bonds and AAA-rated bonds	Federal Reserve Economic Data (FRED) Database
Inflation	Variation rate of the US Consumer Price index	
IPI	Variation rate of the Industrial Production index	
Term_ spread	Term spread between the yield to maturity of a 10-year Treasury note and the three-month Treasury bill	
GDP	Variation rate of US normalised Gross Domestic Product	

Source(s): Own elaboration

this method's estimates are more robust in the presence of outliers, heteroskedasticity and skewness than those of OLS models (Koenker and Hallock, 2001; Koenker, 2005).

The proposed quantile regression model is the following:

$$R_{i,t} = \alpha_\tau + \beta_{1,\tau} EPU_t + \beta_{2,\tau} Cycle_t + \beta_{3,\tau} Default\_spread_t + \beta_{4,\tau} Inflation_t + \beta_{5,\tau} IPI_t + \beta_{6,\tau} Term\_spread_t + \beta_{7,\tau} GDP_t + \varepsilon_{t,\tau}, \quad (1)$$

where R_{it} is the dependent variable of model and represents the stock index i return in month t, α is the constant term, β_k is the regression coefficient corresponding to each explanatory variable k, τ the quantile whose value will be between 0 and 1 (the quantiles 0.25, 0.5 and 0.75 will be taken in the study), and ε_t is the error term in month t.

The previous model allows us to evaluate the impact of EPU on the stock returns analysed. However, to test the role of the economic cycle in the influence of EPU on stock returns, the inclusion of interaction term between EPU and Cycle has been implemented.

We run the regression in Eq. (1) with an additional interaction term given by:

$$R_{i,t} = \alpha_\tau + \beta_{1,\tau} EPU_t + \beta_{2,\tau} EPU_t \cdot Cycle_t + \beta_{3,\tau} Cycle_t + \beta_{4,\tau} Default\_spread_t + \beta_{5,\tau} Inflation_t + \beta_{6,\tau} IPI_t + \beta_{7,\tau} Term\_spread_t + \beta_{8,\tau} GDP_t + \varepsilon_{t,\tau}, \quad (2)$$

To add further robustness to the results from quantile regression, we propose to apply linear regression with OLS. Given the possible heteroskedasticity problem typical of financial series, the OLS models are adjusted for heteroskedasticity (white cross-section standard errors) (Lee and Chen, 2021).

Results and discussion

Basic descriptive statistics

Over the total sample period, the descriptive statistics (Table AI) show how $R_{Large\text{-}Growth}$ and $R_{Small\text{-}Value}$ achieved a higher average return (1% versus 0.9% for $R_{Large\text{-}Value}$ and $R_{Small\text{-}Growth}$). However, when distinguishing by economic cycle, we find that growth stocks had lower losses than value stocks in recessions. In particular, $R_{Large\text{-}Growth}$ recorded the smallest losses (average return of −0.9%). In contrast, larger cap value stocks had the worst results ($R_{Large\text{-}Value}$: −1.8%). Though the average returns of the different types of stocks differ significantly in recessions, the differences recorded in expansions are minimal, with $R_{Small\text{-}Growth}$ obtaining the lowest average return (1.1 versus 1.2% for the rest). These results are in line with evidence shown by Bretschger and Lechthaler (2018), Kirby (2019) and Bianchi (2020). When evaluating the existence of significant differences in the average return of these types of stocks in recessions and expansions, only $R_{Large\text{-}Value}$ has substantial differences depending on the economic cycle, with a significance level of 5%.

Although in recessions the dispersion in all stocks is higher, we identify a clear pattern: the returns of the smallest capitalisation stocks show greater variability, especially those of growth stocks. These results suggest that investment in value stocks may be more advisable in expansions, while growth stocks may perform better in a recession, despite taking on higher risk. In the same vein, Kirby (2019) evidenced a procyclical relation between the expected value premium and expected business conditions.

Table AI shows that EPU has a higher mean value in recessions than in expansions (7.3 vs. 1.3%), although this difference cannot be considered significant. In addition, the dispersion of EPU is greater in recessions than in expansions. In this sense, the literature shows how in recessions, despite the economic policies that will be implemented, uncertainty is higher than in expansions (Baker *et al.*, 2016; Adjei and Adjei, 2017).

Regarding control variables, it should be noted that Default spread and Term spread show significant differences, with a confidence greater than 99% in their mean value depending on the economic cycle. These variables have a higher mean value in recessions (1.7 and 2.2% versus 0.9 and 1.5%, respectively). However, in terms of their dispersion, Default spread has higher variability in recessions (0.9 vs. 0.2%), while Term spread has a higher deviation in expansions (1.1 vs. 0.8%).

IPI and GDP show higher values in expansions (IPI = 0.3% and GDP = 0.2%) than in recessions (IPI = −1.4% and GDP = −0.5%), and these differences are significant at 99%. In both cases, variability is higher in recessions.

Finally, it is worth mentioning that Inflation does not present significant differences in its average for the economic cycle, although in the period studied, it has presented a higher average value in expansions than in recessions (0.2 versus 0.1%).

Table AII shows the bivariate correlations of the variables used. It should be noted that the correlation coefficient between all the explanatory variables among themselves and the dependent variables is low. Only the correlations between IPI and GDP (0.637) and Default spread and Cycle (−0.561) are greater than 0.50 but remain below 0.90, the threshold maximum suggested by Hair *et al.* (2010). Therefore, the multicollinearity problem does not arise in this study.

A more detailed analysis of the bivariate correlations between the different variables indicates how the returns of the four types of stocks are highly correlated with a significance level of less than 1%. In particular, the correlations of $R_{Large\text{-}Value}$ y $R_{Small\text{-}Value}$ (0.859) and $R_{Small\text{-}Value}$ y $R_{Small\text{-}Growth}$ (0.845) stand out.

EPU correlates negatively and significantly with the returns of the four types of stocks, where the strongest correlation is with growth stocks, especially small-cap stocks (−0.270). This result aligns with Hu *et al.* (2018) and Luo and Zhang (2020). More evidence of this result has been found in the literature that examines the impact of investor sentiment on stocks depending on their profile (Lakonishok *et al.*, 1994; Baker and Wurgler, 2006; Waggle and Agrrawal, 2015).

Cycle, as expected given the results in Table AI, is positively and significantly correlated with stock returns (recall Recession = 1 and Expansion = 2). In regard to the rest of the control variables, only GDP is positively and significantly correlated with the returns of the four types of stocks, especially with $R_{Small\text{-}Value}$ (0.204), while Default spread is negatively and significantly correlated only with the returns of value stocks, especially with $R_{Large\text{-}Value}$ (−0.136).

Results of the quantile-based approach

Considering Eq (1), Table 3 shows the results obtained when analysing the influence of EPU on conditional distribution of returns of value and growth stocks of higher and lower capitalisation (PANEL A).

The results show how EPU has a negative and significant impact with a significance level of less than 5% on stock returns, especially small-cap stocks, and between them, growth stocks. Therefore, it is evident that the most determinant characteristic to measure the impact of EPU on stock returns is the larger or smaller capitalisation of the stocks, with smaller capitalisation stocks being the most affected. The literature related to the impact of investor sentiment on stock returns points in the same direction (Lemmon and Portniaguina, 2006; Kumar and Lee, 2006). Though with more minor differences, another determining characteristic in the influence of EPU on stock returns is whether the stocks are value or growth stocks, where the latter are most affected by EPU increases. In this sense, there is evidence that growth stocks are more sensitive to investor sentiment (Lakonishok *et al.*, 1994; Baker and Wurgler, 2006; Wu *et al.*, 2014). Therefore, we accept H1. It can be confirmed that

Variable	$R_{Large\text{-}Value}$ τ_{25} Coef. (*p*-value)	τ_{50} Coef. (*p*-value)	τ_{75} Coef. (*p*-value)	$R_{Large\text{-}Growth}$ τ_{25} Coef. (*p*-value)	τ_{50} Coef. (*p*-value)	τ_{75} Coef. (*p*-value)	$R_{Small\text{-}Value}$ τ_{25} Coef. (*p*-value)	τ_{50} Coef. (*p*-value)	τ_{75} Coef. (*p*-value)	$R_{SmallGrowth}$ τ_{25} Coef. (*p*-value)	τ_{50} Coef. (*p*-value)	τ_{75} Coef. (*p*-value)
PANEL A: Model 3 estimates												
Cons	−0.029 (0.52)	−0.004 (0.84)	−0.027 (0.35)	−0.036 (0.11)	−0.022 (0.53)	0.040** (0.03)	0.025 (0.46)	0.024 (0.55)	0.007 (0.78)	−0.074 (0.13)	0.001 (0.98)	0.009 (0.86)
EPU	−0.056*** (0.01)	−0.046*** (0.00)	−0.031** (0.03)	−0.064*** (0.00)	−0.048*** (0.01)	−0.043*** (0.00)	−0.081*** (0.00)	−0.064*** (0.00)	−0.036*** (0.00)	−0.095*** (0.00)	−0.086*** (0.00)	−0.055** (0.02)
Cycle	0.028 (0.14)	0.016* (0.07)	0.021* (0.08)	0.020** (0.04)	0.021 (0.16)	0.002 (0.78)	0.006 (0.66)	0.002 (0.89)	0.008 (0.40)	0.035* (0.10)	0.007 (0.74)	0.014 (0.51)
Default spread	−3.880*** (0.00)	−1.099* (0.08)	2.449*** (0.01)	−2.488*** (0.00)	−0.163 (0.88)	1.016* (0.06)	−5.548*** (0.00)	−1.405 (0.24)	1.700** (0.01)	−2.546* (0.08)	0.479 (0.74)	1.730 (0.25)
Inflation	−1.544 (0.22)	−0.572 (0.34)	−0.114 (0.89)	0.359 (0.57)	−0.503 (0.62)	−1.442*** (0.01)	−0.034 (0.97)	−0.986 (0.39)	−1.856*** (0.01)	1.800 (0.19)	−0.967 (0.48)	−1.510 (0.29)
IPI	−1.196** (0.02)	−1.095*** (0.00)	−0.599* (0.06)	−0.667*** (0.01)	−0.631 (0.11)	−0.927*** (0.00)	−1.571*** (0.00)	−1.306*** (0.00)	−0.768*** (0.00)	−1.490*** (0.01)	−1.292** (0.02)	−0.727 (0.19)
Term spread	0.125 (0.76)	−0.045 (0.81)	0.058 (0.82)	0.373* (0.06)	−0.158 (0.62)	−0.513*** (0.00)	0.198 (0.52)	0.191 (0.60)	0.321 (0.12)	0.262 (0.55)	−0.019 (0.97)	0.154 (0.73)
GDP	2.711* (0.06)	2.744*** (0.00)	0.245 (0.79)	2.376*** (0.00)	1.760 (0.13)	3.122*** (0.00)	4.387*** (0.00)	4.776*** (0.00)	1.587** (0.03)	3.037* (0.06)	4.038*** (0.01)	0.775 (0.63)
No Obs	317	317	317	317	317	317	317	317	317	317	317	317
PANEL B: Model 4 estimates												
Cons	−0.028 (0.54)	−0.001 (0.95)	0.009 (0.78)	−0.051*** (0.00)	−0.007 (0.81)	0.043** (0.03)	0.025 (0.41)	0.028 (0.37)	−0.008 (0.73)	−0.076 (0.16)	−0.018 (0.65)	0.029 (0.51)
EPU	−0.054 (0.53)	−0.179*** (0.00)	−0.149** (0.02)	−0.131*** (0.00)	−0.122** (0.02)	−0.190*** (0.00)	−0.088 (0.13)	−0.169*** (0.01)	−0.183*** (0.00)	−0.081 (0.43)	−0.280*** (0.00)	−0.293*** (0.00)
EPU - Cycle	−0.001 (0.98)	0.074*** (0.00)	0.067* (0.05)	0.037** (0.03)	0.041 (0.16)	0.078*** (0.00)	0.006 (0.84)	0.062* (0.06)	0.075*** (0.00)	−0.012 (0.83)	0.119*** (0.01)	0.127*** (0.01)
Cycle	0.028 (0.15)	0.016* (0.09)	0.006 (0.66)	0.027*** (0.00)	0.015 (0.21)	0.001 (0.91)	0.007 (0.59)	−0.003 (0.80)	0.015 (0.14)	0.036 (0.12)	0.015 (0.38)	0.007 (0.70)
Default spread	−3.865*** (0.00)	−1.367*** (0.03)	1.659* (0.09)	−2.442*** (0.00)	−0.532 (0.52)	1.008* (0.09)	−5.662*** (0.00)	−0.437 (0.64)	1.779** (0.01)	−2.367 (0.14)	0.652 (0.58)	0.974 (0.46)
Inflation	−1.563 (0.22)	−0.454 (0.45)	−0.390 (0.67)	0.573 (0.20)	−0.393 (0.61)	−1.132** (0.04)	−0.045 (0.96)	−1.070 (0.23)	−1.772*** (0.01)	1.523 (0.31)	−0.900 (0.41)	−1.302 (0.30)
IPI	−1.172** (0.02)	−1.009*** (0.00)	−0.718** (0.05)	−0.882*** (0.00)	−0.533* (0.08)	−0.898*** (0.00)	−1.712*** (0.00)	−1.044*** (0.00)	−0.776*** (0.00)	−1.610*** (0.01)	−0.856** (0.05)	−0.529 (0.28)
Term spread	0.114 (0.77)	−0.028 (0.88)	0.038 (0.90)	0.431*** (0.00)	−0.142 (0.56)	−0.560*** (0.00)	0.248 (0.35)	0.215 (0.44)	0.329 (0.12)	0.232 (0.63)	0.224 (0.52)	0.104 (0.79)
GDP	2.714* (0.07)	1.913*** (0.01)	1.159 (0.28)	2.054*** (0.00)	1.234 (0.17)	2.192*** (0.00)	4.470*** (0.00)	3.646*** (0.00)	1.524** (0.05)	4.033** (0.02)	2.304* (0.07)	0.486 (0.74)
No Obs	317	317	317	317	317	317	317	317	317	317	317	317

Note(s): ***, ** and * indicate the significance at 1%, 5% and 10% levels, respectively
Source(s): Own elaboration

Table 3.
Estimates of the quantile regression models

the impact of EPU is not the same for all types of stocks, with growth and small-cap stocks being the most sensitive to changes in EPU and larger cap value stocks being least affected by EPU. These results align with Hu *et al.* (2018) and Luo and Zhang (2020).

The application of quantile regression additionally allows us to evaluate the impact on different levels of the dependent variable. The results show that the stocks with the lowest returns (quantile 0.25) are more sensitive to EPU in all cases, with the lowest returns of growth and small-cap stocks being the most affected by EPU increases. Specifically, in this type of stock, a 1-point increase in EPU is associated with a −9.5% reduction in return. Thus, we accept H2 partially. These results are in line with Bekiros *et al.* (2016) and Raza *et al.* (2018). The under and overreaction of stock returns come from a financial context resulting from Economic Policy Uncertainty (Barberis *et al.*, 1998; Lewellen, 2002), leading to a different dependence structure across the stock return distribution (Baur *et al.*, 2012; Guo *et al.*, 2018).

There is no unified pattern for all stocks in regard to economic cycle. In growth stocks, the economic cycle has a positive and significant impact on the lowest return stocks; however, in the case of value stocks, only the largest capitalisation and stocks with the highest returns are influenced by this variable. These results show that the growth stocks with the smallest capitalisation and lowest return and value stocks with the highest capitalisation and return are most sensitive to changes in the economic cycle (Bekiros *et al.*, 2016). The result of growth stocks aligns with previous literature (Kirby, 2019; Bianchi, 2020). For value stocks, a broad literature shows that the historical excess return of value stocks over growth stocks (the denominated HML-factor) is statistically associated with economic growth (Bretschger and Lechthaler, 2018).

For the rest of the control variables, it should be noted that Default spread has a negative impact on the return of the lowest return stocks but a positive impact on the highest return stocks (except for growth and small-cap stocks, with value stocks being the most affected, especially small-cap stocks). IPI has a negative and significant impact on stock returns, especially on smaller cap, profitable and value stocks. Finally, GDP has a positive impact on the return of smaller cap stocks and lower returns, especially value stocks.

Examining the results obtained by including the interaction term Eq. (2) (PANEL B), we can observe how the economic cycle moderates the impact of EPU on stock returns, i.e. in expansions, the impact of EPU on stock returns is diluted, as previous literature has shown (Baker *et al.*, 2016; Adjei and Adjei, 2017). So, the negative impact of EPU is lesser in expansions than in recessions. Looking at the different types of stocks, we show how the economic cycle moderates the impact of EPU on the return of growth and small-cap stocks. We therefore accept H3. These results indicate the higher sensitivity of growth and lower cap stocks, confirming evidence shown by Roh *et al.* (2019) and Bianchi (2020).

However, this moderating effect is in general only present when stocks have higher returns. Therefore, we accept H4. Baker and Wurgler (2006) evidenced a similar behaviour in relation to investor sentiment. This means that the moderating effect of the economic cycle gradually loses its impact as the stock market tends to be more bearish. This is the advantage of using the quantile approach, as it can capture more factors of uncertainty and provide more granular and detailed empirical results. Furthermore, Bekiros *et al.* (2016) show the importance of business cycle fluctuations in EPU predictive power in a quantile regression.

Results of the OLS regression analysis

To add further robustness to the results, OLS with heteroskedasticity correction has been applied. Table 4 shows the results obtained by applying this method.

The results show how EPU has a negative and significant impact with a significance level of less than 1% on stock returns, especially in growth and small-cap stocks. Without considering the possible moderating effect of the economic cycle, it is shown how a 1-point

Variable	(1) Coef. (*p*-value)	$R_{Large\text{-}Value}$ Std. Dev	(2) Coef. (*p*-value)	Std. Dev	(1) Coef. (*p*-value)	$R_{Large\text{-}Growth}$ Std. Dev	(2) Coef. (*p*-value)	Std. Dev	(1) Coef. (*p*-value)	$R_{Small\text{-}Value}$ Std. Dev	(2) Coef. (*p*-value)	Std. Dev	(1) Coef. (*p*-value)	$R_{Small\text{-}Growth}$ Std. Dev	(2) Coef. (*p*-value)	Std. Dev
Cons	−0.015 (0.53)	0.023	−0.007 (0.74)	0.020	0.016 (0.58)	0.029	0.013 (0.65)	0.455	0.005 (0.86)	0.028	0.017 (0.46)	0.022	0.009 (0.82)	0.040	0.008 (0.79)	0.032
EPU	−0.037*** (0.00)	0.011	−0.133*** (0.01)	0.049	−0.041*** (0.00)	0.014	−0.175*** (0.01)	−2.609	−0.052*** (0.00)	0.013	−0.143*** (0.01)	0.052	−0.058*** (0.00)	0.019	−0.227*** (0.00)	0.037
EPU . Cycle			0.052* (0.05)	0.026			0.069* (0.06)	1.915			0.047 (0.11)	0.029			0.087*** (0.00)	0.024
Cycle	0.020** (0.04)	0.010	0.017** (0.04)	0.008	0.007 (0.59)	0.012	0.007 (0.56)	0.584	0.008 (0.48)	0.012	0.004 (0.63)	0.009	0.005 (0.77)	0.017	0.004 (0.76)	0.013
Default spread	−1.425* (0.098)	0.858	−1.261 (0.15)	0.866	−1.734* (0.08)	0.974	−1.581 (0.11)	−1.593	−0.928 (0.39)	1.083	−1.276 (0.24)	1.076	−0.702 (0.60)	1.352	−0.375 (0.76)	1.248
Inflation	−0.505 (0.39)	0.587	−0.955* (0.10)	0.573	−0.201 (0.76)	0.670	−0.489 (0.48)	0.711	−0.623 (0.40)	0.732	−0.911 (0.20)	0.713	−0.423 (0.65)	0.933	−0.678 (0.47)	0.931
IPI	−0.800*** (0.00)	0.278	−0.922*** (0.00)	0.240	−0.325 (0.36)	0.357	−0.290 (0.39)	−0.855	−0.950*** (0.00)	0.310	−0.983*** (0.00)	0.321	−0.574 (0.16)	0.403	−0.512 (0.11)	0.321
Term spread	0.071 (0.70)	0.183	0.061 (0.74)	0.181	−0.067 (0.77)	0.225	−0.048 (0.83)	−0.216	0.112 (0.62)	0.224	0.106 (0.68)	0.253	0.035 (0.92)	0.333	0.081 (0.79)	0.303
GDP	2.509*** (0.01)	0.925	2.306*** (0.00)	0.631	2.228*** (0.01)	0.792	2.307* (0.07)	1.825	3.278*** (0.00)	1.120	3.769*** (0.00)	1.046	2.906*** (0.00)	1.013	2.407*** (0.00)	0.338
No Obs	317		317		317		317		317		317		317		317	
R^2	0.108		0.196		0.099		0.116		0.096		0.155		0.078		0.884	
Durbin–Watson	1.973		1.982		1.958		1.993		1.895		1.912		1.937		1.952	

Note(s): ***, ** and * indicate the significance at 1%, 5% and 10% levels, respectively
Source(s): Own elaboration

Table 4.
Estimates of the OLS regression models with heteroscedasticity correction

increase in EPU is associated with a reduction of −5.8% in the return of small-cap growth stocks, −5.2% in small-cap value stocks, −4.1% in large-cap growth stocks and −3.7% in large-cap value stocks.

When we include the interaction of EPU with Cycle, we observe how the economic cycle moderates the impact of EPU on stock returns, especially in the case of growth stocks with the lowest capitalisation.

In the end, we can determine that these findings remain robust when the methodology changes. As noted, in addition to the advantages of quantile regression (i.e. more robust estimates in the presence of outliers, heteroskedasticity and skewness), this methodology has allowed us to analyse the influence of EPU during the economic cycle on different stocks, considering their level of return. This particularity, not present in models based on conditional expectation, has allowed us to analyse the dependence structure in bull and bear markets.

Conclusions

Understanding the impact of EPU on stock returns considering stock typology and the role played by the economic cycle under different circumstances can help investors make better investment decisions. In this paper, we also employ a quantile regression model to analyse how EPU affects growth/value and small/large-caps stock returns under bearish (lower quantiles) and bullish (higher quantiles) markets differentiated by periods of recession and expansion.

According to the research objectives, the conclusions are as follows: first, the negative sensitivity pattern of EPU on stock returns is moderated by the economic cycle, especially for growth and small stocks, with higher impact during recessions, in line with the existing literature (Kelly, 2003; Aretz *et al.*, 2010). Second, the economic cycle moderates negative EPU impact only on the most profitable stocks. This moderation loses its effect as stock prices achieve lower returns, with minimal effects experienced at the lower tail of the stock return distribution. These findings deepen our knowledge about the behaviour of the extreme stocks under EPU, contributing to the literature and expanding on the work of Bekiros *et al.* (2016), Raza *et al.* (2018) and Huang and Liu (2022), among others.

This research has several implications. A better understanding of the asymmetry and extreme effect of EPU on stock market returns considering stock type can help investors improve and optimise portfolio allocation decisions. Moreover, this paper sheds further light on investment strategies that pursue opportunities arising from a changing economic cycle, especially for extreme stocks. Our findings show that investment in growth stocks is only advisable in times of expansion and low EPU. However, in times of recession and high EPU, investment in large cap and value stocks will likely be more stable to deal with the uncertain environment characterised by high EPU.

The limitations of this study relate to the data sample corresponding only to the US stock market and the consideration of different moderating variables. In terms of the study period, one approach could be to analyse two different periods of time to examine the emergence of technology companies becoming powerful growth stocks and an important factor driving stock market returns since the early 2000s. A comparison of a period before and after the emergence of these technology companies could present different outcomes, especially during recessions.

Future research could take several directions, one being to analyse the opportunities that arise from an increase/decrease in EPU impact on value premium strategies considering the changes in the economic cycle. Another approach could explore the profitability of different types of stocks under extreme risk. Lastly, investigating other methodological approaches, including a different moderating variable, could result in a better understanding of the relationship between uncertainty and growth/value and small/large cap stocks.

References

Aboura, S. and Arisoy, Y.E. (2017), "Does aggregate uncertainty explain size and value anomalies?", *Applied Economics*, Vol. 49 No. 32, pp. 3214-3230, doi: 10.1080/00036846.2016.1257107.

Adjei, F.A. and Adjei, M. (2017), "Economic policy uncertainty, market returns and expected return predictability", *Journal of Financial Economic Policy*, Vol. 9 No. 3, pp. 242-259, doi: 10.1108/JFEP-11-2016-0074.

Adjei, A.N.K., Tweneboah, G. and Owusu Junior, P. (2022), "Interdependence of economic policy uncertainty and business cycles in selected emerging market economies", *Journal of Financial Economic Policy*, Vol. 14 No. 5, pp. 601-632, doi: 10.1108/JFEP-07-2021-0193.

Ahmad, W. and Sharma, S.K. (2018), "Testing output gap and economic uncertainty as an explicator of stock market returns", *Research in International Business and Finance*, Vol. 45, pp. 293-306, doi: 10.1016/j.ribaf.2017.07.162.

Alcázar-Blanco, A.C., Paule-Vianez, J., Prado-Román, M. and Coca-Pérez, J.L. (2021), "Generalized regression neuronal networks to predict the value of numismatic assets. Evidence for the walking liberty half dollar", *European Research on Management and Business Economics*, Vol. 27 No. 3, 100167, doi: 10.1016/j.iedeen.2021.100167.

Antonakakis, N., Chatziantoniou, I. and Filis, G. (2013), "Dynamic co-movements of stock market returns, implied volatility and policy uncertainty", *Economics Letters*, Vol. 120 No. 1, pp. 87-92, doi: 10.1016/j.econlet.2013.04.004.

Aretz, K., Bartram, S.M. and Pope, P.F. (2010), "Macroeconomic risks and characteristic-based factor models", *Journal of Banking and Finance*, Vol. 34 No. 6, pp. 1383-1399, doi: 10.1016/j.jbankfin.2009.12.006.

Arouri, M., Estay, C., Rault, C. and Roubaud, D. (2016), "Economic policy uncertainty and stock markets: long-run evidence from the US", *Finance Research Letters*, Vol. 18, pp. 136-141, doi: 10.1016/j.frl.2016.04.011.

Baker, M. and Wurgler, J. (2006), "Investor sentiment and the cross-section of Stock Returns", *The Journal of Finance*, Vol. 61 No. 4, pp. 1645-1680, doi: 10.1111/j.1540-6261.2006.00885.x.

Baker, S.R., Bloom, N. and Davis, S.J. (2016), "Measuring economic policy uncertainty", *The Quarterly Journal of Economics*, Vol. 131 No. 4, pp. 1593-1636, doi: 10.1093/qje/qjw024.

Barberis, N., Shleifer, A. and Vishny, R. (1998), "A model of investor sentiment", *Journal of Financial Economics*, Vol. 49 No. 3, pp. 307-343, doi: 10.1016/S0304-405X(98)00027-0.

Bathia, D. and Bredin, D. (2013), "An examination of investor sentiment effect on G7 stock market returns", *The European Journal of Finance*, Vol. 19 No. 9, pp. 909-937, doi: 10.1080/1351847X.2011.636834.

Baur, D.G., Dimpfl, T. and Jung, R.C. (2012), "Stock return autocorrelations revisited: a quantile regression approach", *Journal of Empirical Finance*, Vol. 19 No. 2, pp. 254-265, doi: 10.1016/j.jempfin.2011.12.002.

Bekiros, S. and Gupta, R. (2015), "Predicting stock returns and volatility using consumption-aggregate wealth ratios: a nonlinear approach", *Economics Letters*, Vol. 131, pp. 83-85, doi: 10.1016/j.econlet.2015.03.019.

Bekiros, S., Gupta, R. and Majumdar, A. (2016), "Incorporating economic policy uncertainty in US equity premium models: a nonlinear predictability analysis", *Finance Research Letters*, Vol. 18, pp. 291-296, doi: 10.1016/j.frl.2016.01.012.

Beugelsdijk, S. and Frijns, B. (2010), "A cultural explanation of the foreign bias in international asset allocation", *Journal of Banking and Finance*, Vol. 34 No. 9, pp. 2121-2131, doi: 10.1016/j.jbankfin.2010.01.020.

Bianchi, F. (2020), "The great depression and the great recession: a view from financial markets", *Journal of Monetary Economics*, Vol. 114, pp. 240-261, doi: 10.1016/j.jmoneco.2019.03.010.

Bretschger, L. and Lechthaler, F. (2018), "Stock performance and economic growth: lessons from the Japanese case", *Macroeconomics and Finance in Emerging Market Economies*, Vol. 11 No. 2, pp. 195-217, doi: 10.1080/17520843.2017.1356343.

Brogaard, J. and Detzel, A. (2015), "The asset-pricing implications of government economic policy uncertainty", *Management Science*, Vol. 66 No. 1, pp. 3-18, doi: 10.1287/mnsc.2014.2044.

Brown, G.W. and Cliff, M.T. (2005), "Investor sentiment and asset valuation", *The Journal of Business*, Vol. 78 No. 2, pp. 405-440, doi: 10.1086/427633.

Chen, J., Jiang, F. and Tong, G. (2018), "Economic policy uncertainty in China and stock market expected returns", *Accounting and Finance*, Vol. 57 No. 5, pp. 1265-1286, doi: 10.1111/acfi.12338.

Cheng, H.P. and Yen, K.C. (2020), "The relationship between the economic policy uncertainty and the cryptocurrency market", *Finance Research Letters*, Vol. 35, 101308, doi: 10.1016/j.frl.2019.101308.

Crain, M.A. (2011), "A literature review of the size effect", *SSRN Electronic Journal*. doi: 10.2139/ssrn.1710076.

Fama, E.F. and French, F.R. (1989), "Business conditions and expected returns on stocks and bonds", *Journal of Financial Economics*, Vol. 25 No. 1, pp. 23-49, doi: 10.1016/0304-405X(89)90095-0.

Fama, E.F. and French, K.R. (1992), "The cross-section of expected stock returns", *Journal of Finance*, Vol. 67, pp. 427-465, doi: 10.1111/j.1540-6261.1992.tb04398.x.

Guo, P., Zhu, H. and You, W. (2018), "Asymmetric dependence between economic policy uncertainty and stock market returns in G7 and BRIC: a quantile regression approach", *Finance Research Letters*, Vol. 25, pp. 251-258, doi: 10.1016/j.frl.2017.11.001.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2010), *Multivariate Data Analysis*, 7 ed., Prentice Hall, Upper Saddle River, NJ.

Hu, Z., Kutan, A.M. and Sun, P.W. (2018), "Is US economic policy uncertainty priced in China's A-shares market? Evidence from market, industry, and individual stocks", *International Review of Financial Analysis*, Vol. 57, pp. 207-220, doi: 10.1016/j.irfa.2018.03.015.

Huang, W.Q. and Liu, P. (2022), "Asymmetric effects of economic policy uncertainty on stock returns under different market conditions: evidence from G7 stock markets", *Applied Economics Letters*, Vol. 29 No. 9, pp. 780-784, doi: 10.1080/13504851.2021.1885606.

International Monetary Fund (2013), *World Economic Outlook: Hopes, Realities, Risks*. IMF Press, available at: https://www.imf.org/external/pubs/ft/weo/2013/01/

Ioannidis, C. and Ka, K. (2021), "Economic policy uncertainty and bond risk premia", *Journal of Money, Credit and Banking*, Vol. 53 No. 6, pp. 1479-1522, doi: 10.1111/jmcb.12748.

Jiang, G., Lee, C.M. and Zhang, Y. (2005), "Information uncertainty and expected returns", *Review of Accounting Studies*, Vol. 10 Nos 2-3, pp. 185-221, doi: 10.1007/s11142-005-1528-2.

Jiang, Y., Tian, G., Wu, Y. and Mo, B. (2022), "Impacts of geopolitical risks and economic policy uncertainty on Chinese tourism-listed company stock", *International Journal of Finance and Economics*, Vol. 27 No. 1, pp. 320-333, doi: 10.1002/ijfe.2155.

Kang, W. and Ratti, R. (2013), "Oil shocks, policy uncertainty and stock market return", *Journal of International Financial Markets, Institutions and Money*, Vol. 26 No. 14, pp. 305-318, doi: 10.1016/j.intfin.2013.07.001.

Kannadhasan, M. and Das, D. (2020), "Do Asian emerging stock markets react to international economic policy uncertainty and geopolitical risk alike? A quantile regression approach", *Finance Research Letters*, Vol. 34, 101276, doi: 10.1016/j.frl.2019.08.024.

Kelly, P.J. (2003), "Real and inflationary macroeconomic risk in the Fama and French size and book-to-market portfolios", *EFMA 2003 Helsinki Meetings*, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=407800

Keynes, J.M. (1937), "The general theory of employment", *The Quarterly Journal of Economics*, Vol. 51 No. 2, pp. 209-223, doi: 10.2307/1882087.

Killins, R.N., Ngo, T. and Wang, H. (2022), "Politics and equity markets: evidence from Canada", *Journal of Multinational Financial Management*, Vol. 63, 100726, doi: 10.1016/j.mulfin.2021.100726.

Kim, M.K. and Burnie, D.A. (2002), "The firm size effect and the economic cycle", *Journal of Financial Research*, Vol. 25 No. 1, pp. 111-124, doi: 10.1111/1475-6803.00007.

Kirby, C. (2019), "The value premium and expected business conditions", *Finance Research Letters*, Vol. 30, pp. 360-366, doi: 10.1016/j.frl.2018.10.022.

Koenker, R. (2005), *Quantile Regression. Econometric Society Monograph Series 38*, Cambridge University Press, Cambridge.

Koenker, R. and Hallock, K.F. (2001), "Quantile regression", *Journal of Economic Perspectives*, Vol. 15 No. 4, pp. 143-156, doi: 10.1257/jep.15.4.143.

Kumar, A. and Lee, C.M. (2006), "Retail investor sentiment and return comovements", *The Journal of Finance*, Vol. 61 No. 5, pp. 2451-2486, doi: 10.1111/j.1540-6261.2006.01063.x.

Kumar, A., Page, J.K. and Spalt, O.G. (2012), "Investor sentiment and return comovements: evidence from stock splits and headquarters changes", *Review of Finance*, Vol. 17 No. 3, pp. 921-953, doi: 10.1093/rof/rfs010.

Kurov, A. and Stan, R. (2018), "Monetary policy uncertainty and the market reaction to macroeconomic news", *Journal of Banking and Finance*, Vol. 86, pp. 127-142, doi: 10.1016/j.jbankfin.2017.09.005.

Lakonishok, J., Shleifer, A. and Vishny, R.W. (1994), "Contrarian investment, extrapolation, and risk", *The Journal of Finance*, Vol. 49 No. 5, pp. 1541-1578, doi: 10.1111/j.1540-6261.1994.tb04772.x.

Lee, C.C. and Chen, M.P. (2021), "The effects of investor attention and policy uncertainties on cross-border country exchange-traded fund returns", *International Review of Economics and Finance*, Vol. 71, pp. 830-852, doi: 10.1016/j.iref.2020.10.015.

Lee, J.H. and Kim, R. (2017), "Dynamic style allocation under the regime shifts: value vs growth", *Asian Review of Financial Research*, Vol. 30 No. 3, pp. 103-135, doi: 10.37197/arfr.2017.30.3.4.

Lemmon, M. and Portniaguina, E. (2006), "Consumer confidence and asset prices: some empirical evidence", *The Review of Financial Studies*, Vol. 19 No. 4, pp. 1499-1529, doi: 10.1093/rfs/hhj038.

Lewellen, J. (2002), "Momentum and autocorrelation in stock returns", *The Review of Financial Studies*, Vol. 15 No. 2, pp. 533-564, doi: 10.1093/rfs/15.2.533.

Li, X.L., Balcilar, M., Gupta, R. and Chang, T. (2015), "The causal relationship between economic policy uncertainty and stock returns in China and India: evidence from a bootstrap rolling window approach", *Emerging Markets Finance and Trade*, Vol. 52 No. 3, pp. 674-689, doi: 10.1080/1540496X.2014.998564.

Luo, Y. and Zhang, C. (2020), "Economic policy uncertainty and stock price crash risk", *Research in International Business and Finance*, Vol. 51, 101112, doi: 10.1016/j.ribaf.2019.101112.

Neves, M.E., Abreu Pinto, M., Assunção Fernandes, C.M.d. and Simões Vieira, E.F. (2021), "Value and growth stock returns: international evidence (JES)", *International Journal of Accounting and Information Management*, Vol. 29 No. 5, pp. 698-733, doi: 10.1108/IJAIM-05-2021-0097.

Pastor, L. and Veronesi, P. (2013), "Political uncertainty and risk premia", *Journal of Finance Economic*, Vol. 110, pp. 520-545, doi: 10.1016/j.jfineco.2013.08.007.

Paule-Vianez, J., Prado-Román, C. and Gómez-Martínez, R. (2020), "Economic policy uncertainty and Bitcoin. Is Bitcoin a safe-haven asset?", *European Journal of Management and Business Economics*, Vol. 29 No. 3, pp. 347-363, doi: 10.1108/EJMBE-07-2019-0116.

Paule-Vianez, J., Lobão, J., Gómez-Martínez, R. and Prado-Román, C. (2021), "Momentum strategies in times of economic policy uncertainty", *Journal of Financial Economic Policy*, Vol. 13 No. 3, pp. 285-300, doi: 10.1108/JFEP-10-2019-0198.

Pham, L. and Nguyen, C.P. (2022), "How do stock, oil, and economic policy uncertainty influence the green bond market?", *Finance Research Letters*, Vol. 45, 102128, doi: 10.1016/j.frl.2021.102128.

Qadan, M. and Aharon, D.Y. (2019), "Can investor sentiment predict the size premium?", *International Review of Financial Analysis*, Vol. 63, pp. 10-26, doi: 10.1016/j.irfa.2019.02.005.

Raza, S.A., Zaighum, I. and Shah, N. (2018), "Economic policy uncertainty, equity premium and dependence between their quantiles: evidence from quantile-on-quantile approach", *Physica A: Statistical Mechanics and its Applications*, Vol. 492, pp. 2079-2091, doi: 10.1016/j.physa.2017.11.125.

Roh, T.Y., Lee, C. and Min, B.K. (2019), "Consumption growth predictability and asset prices", *Journal of Empirical Finance*, Vol. 51, pp. 95-118, doi: 10.1016/j.jempfin.2019.02.001.

Scheurle, P. and Spremann, K. (2010), "Size, book-to-market, and momentum during the business cycle", *Review of Managerial Science*, Vol. 4, pp. 201-215, doi: 10.1007/s11846-010-0041-6.

Smales, L.A. (2017), "The importance of fear: investor sentiment and stock market returns", *Applied Economics*, Vol. 49 No. 34, pp. 3395-3421, doi: 10.1080/00036846.2016.1259754.

Song, G.H. (2023), "Size premium or size discount?–A dynamic capital mobility based interpretation", *Studies in Economics and Finance*, Vol. 40 No. 2, pp. 266-285, doi: 10.1108/SEF-04-2022-0211.

Switzer, L.N. (2010), "The behaviour of small cap vs. large cap stocks in recessions and recoveries: empirical evidence for the United States and Canada", *The North American Journal of Economics and Finance*, Vol. 21 No. 3, pp. 332-346, doi: 10.1016/j.najef.2010.10.002.

Van Dijk, M.A. (2011), "Is size dead? A review of the size effect in equity returns", *Journal of Banking and Finance*, Vol. 35 No. 12, pp. 3263-3274, doi: 10.1016/j.jbankfin.2011.05.009.

Waggle, D. and Agrrawal, P. (2015), "Investor sentiment and short-term returns for size-adjusted value and growth portfolios", *Journal of Behavioral Finance*, Vol. 16 No. 1, pp. 81-93, doi: 10.1080/15427560.2015.1000329.

Wu, D.D., Zheng, L. and Olson, D.L. (2014), "A decision support approach for online stock forum sentiment analysis", *IEEE Transactions on Systems Man and Cybernetics Systems*, Vol. 44 No. 8, pp. 1077-1087, doi: 10.1109/TSMC.2013.2295353.

Supplementary material

The supplementary material for this article can be found online.

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The consumer intention to use e-commerce applications in the post-pandemic era: a predictive approach study using a CHAID tree-based algorithm

Received 15 December 2022
Revised 21 February 2023
15 May 2023
3 September 2023
20 September 2023
Accepted 26 September 2023

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Abstract

Purpose – This study proposes a hierarchic segmentation that develops a tree-based classification model and classifies the cases into groups. This allows for the definition of e-commerce user profiles for each of the groups. Additionally, it facilitates the development of actions to improve the adoption of the online channel that is in such high demand in the current pandemic COVID-19 context.

Design/methodology/approach – Regarding the created segments, two extreme segments stand out due to their marked differences and high volume. Segment 3 with 23% of the sample is the group with the most predisposition to use the online channel and is characterised by a high level of trust, more habitual use in comparison with other groups and the belief that its use implies high performance, which indicates they believe it to be useful, quick and helpful for more an effective shopping experience. The other extreme is found in segment 7. This group makes up 17.7% of the total and is the most reluctant to use the online channel. These users are characterised by the complete opposite: they have a low level of trust in this channel. However, the effort expectancy is low, i.e. they consider that the adoption of the online channel does not involve many difficulties in its learning and use. Nevertheless, they use it less regularly than the others.

Findings – Based on the conclusions reached in this study, in the current pandemic context in which consumer demand for online shopping channels for all types of products is on the rise, it is recommended that companies focus on the following aspects. It is essential to build trust with the user and show them the real benefits of e-commerce, how it would improve their life and why they should use it. Additionally, it is vital that the user perceives it as an easy procedure that does not require a significant learning curve. Other fundamental aspects would be to reduce any uncertainty the user might have about the online shopping process, to make it as easy as possible, and to design a simple, intuitive and user-friendly interface. It is also recommendable to manage data usage efficiently. To do so, the authors recommend asking the user for the least amount of information possible,

European Journal of Management and Business Economics
Vol. 34 No. 1, 2025
pp. 103-119
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-12-2022-0375

offering a data protection policy and assuring them that their information will not be misused nor shared with third parties. All of this provides a series of facilities to modify the online shopping habits of users.

Research limitations/implications – As in most of the research, this study presents a series of limitations that should be debated and that could open future lines of investigation. Firstly, regarding the sample used that was limited to two neighbouring countries with similar profiles *a priori*; it would be necessary to compare their possible cultural differences according to Hofstede's dimensions as well as increase the number of European countries being analysed to reach a more generalised conclusions. Secondly, the variables used are a combination of those derived from the UTAUT2 model and others suggested in the literature as decisive in technology adoption by users, in this sense other theories and variables could be incorporated to complete a more holistic model.

Practical implications – This work contributes in a general way to (1) analysing the intention to use e-commerce platforms from a set of antecedents previously defined by their importance, after a period of economic and social restrictions derived from the pandemic; (2) determination of customer segments from the classification made by the CHAID analysis; (3) characterisation of the previously defined segments through the successive divisions that were proposed in the analysis carried out.

Social implications – Other fundamental aspects would be to reduce any uncertainty the user might have about the online shopping process to make it as easy as possible, and to design a simple, intuitive, and user-friendly interface. It is also recommended to manage data usage efficiently. To do so, the authors recommend asking the user for the least amount of information possible, offering a data protection policy, and assuring them that their information will not be misused or shared with third parties.

Originality/value – The results obtained have allowed us to establish predictive and explanatory models of the behaviour of the segments and profiles created, which will help companies to improve their relationships with online customers in the coming years.

Keywords User-intention, E-commerce, Segmentation, Trust, CHAID, COVID-19

Paper type Research paper

1. Introduction

The COVID-19 pandemic and the effects it has had on healthcare, society, and the economy are producing a change in consumer shopping habits. The increase in the general use of e-commerce reveals a greater tendency towards online shopping among consumers, even amongst those who would not usually make use of these forms of shopping. In Portugal, just 38.7% of the population between the ages of 16 and 74 years shopped online in 2019, a much lower percentage than the European average of 63%, or in the case of Spain which was close to 60% (Statista, 2020). However, the effect of the pandemic caused a 40%–60% increase in e-commerce, compared to the figures in 2019, especially in food-related products (ICEX, 2020). In the year of the pandemic, 2020, online retail sales, excluding food, grew in Europe by an average of 31%. Spain was the country with the second-highest increase, with growth reaching 38% (Wyman, 2021). According to this report, although physical stores will continue to be the primary retail channel in this decade, the observed growth in the online channel during the pandemic has demonstrated the ability of e-commerce to adapt to our environment, leading us to imagine a multi-channel future for retail. Consumers have increased their level of trust in online commerce, forcing physical distributors to include online functions to increase the attractiveness of their products that are increasingly integrated into the on-offline context.

The consumers' adoption of a technology is decisive in its success. Therefore, if we know the factors that affect their adoption and their intention of use, we will be able to facilitate an improved implementation in companies and a greater acceptance by the consumers/users. In this study we drew from the classic theories on acceptance of technology: The technology acceptance model, TAM (Davis, 1985, 1989) and the theory of planned behaviour, TPB (Ajzen, 1991), the proposed model in the Unified Theory of Adoption and Use of Technology, UTAUT (Venkatesh *et al.*, 2003) and its extended version UTAUT2 (Venkatesh *et al.*, 2012) that comprises the most significant contributions to the previous models. The changes caused by COVID-19 and its consequences suggest that there are other variables that increase and improve the intention of using e-commerce amongst online consumers.

This research analyses the gap generated the line between physical stores and e-commerce is ever more blurred. Based on the discussions we proposed the following research questions (RQs).

RQ1. This study will enable us to identify the factors that affect the adoption, and use of e-commerce by consumers and the decision to shop online. This investigation deepens the examination of the critical factors affecting the adoption of electronic commerce amongst these users.

RQ2. Additionally, it aims to discover if there is an unobserved heterogeneity in consumer behaviour and, if this is the case, to find relevant segments of e-commerce adopters in the post-COVID-19 era.

RQ3. Once we have identified the different behaviour segments that are influenced by the proposed variables in the model and understood the profile of these groups, we will recommend strategies to e-commerce platforms and app developers to improve consumer commitment to use said tools.

Consequently, the objective of the research is twofold. First, to increase our understanding of online consumer engagement and the relevant segments, we have added new original variables as inhibiting and influencing factors to obtain a more explanatory and predictive model of e-commerce adoption and usage in the post-COVID-19 era. Secondly, once the most relevant segments have been determined, strategies will be established for the different stakeholders involved in the online business.

In order to reach the objective of this research, two groups of variables were established: on one hand, a group of behaviour-related variables divided between facilitating variables (performance expectancy, effort expectancy, social influence, habit, facilitating conditions, hedonic motivation and trust) and variables considered to be obstacles in e-commerce (privacy risk, switching cost, perceived risk and technophobia); and on the other hand, a group of variables related to the socio-demographic characteristics of the users in both countries (gender, age, level of education, size of household and size of the municipality). In this way, this group of variables will enable the observation of both the behavioural variables, either facilitating or obstructing to adoption, and the socio-demographic variables.

To this effect, this investigation is structured in the following manner: following on from the introduction above, in the second section we analyse the fundamental concepts associated with the investigation and that are related to the segmentation in question; the third section presents the methodology framework used, while the fourth section analyses the major results of the empirical work. Finally, the last section presents the conclusions, implications, limitations, and future lines of research.

2. Literature review

2.1 Socio-demographic characteristics as segmentation variables

To reach the objectives of the investigation, it is proposed that the primary socio-demographic variables be included in the study in addition to those previously mentioned. The scientific literature reveals a strong association between socio-demographic characteristics and the adoption of different technologies (for example: Guttentag and Smith, 2020; Molinillo *et al.*, 2020; Choi, 2021). The socio-demographic factors of the respondents, such as gender, age, level of education, size of household and size of the municipality are influencing factors in the intention to adopt and the intention to continue using a technology.

Gender has been used as a segmentation variable in the scope of technology usage since the research done by Venkatesh and Morris (2000). Men and women have different

commercial orientations that lead to different behaviours (Molinillo *et al.*, 2021). According to social psychology, men are more pragmatic and highly task and result-orientated than women are (Ramkissoon and Nunkoo, 2012) which implies behavioural differences in their actions. Traditionally, men have been more willing to participate in e-commerce than women (Susskind, 2004), make a greater number of purchases (Hasan, 2010), have a higher tendency to thoughtful purchasing (Zhou *et al.*, 2007), are more utilitarian and are more daring when making decisions (Lynott and McCandless, 2000) although women are more reliable (Escobar-Rodríguez *et al.*, 2017).

On the other hand, age is another fundamental variable for defining the intention of technology usage (Phang *et al.*, 2006). In this regard, older users usually tend to be relatively relaxed in terms of using technology to carry out transactions because they are sceptical about technology and rely more on offline transactions (Chawla and Joshi, 2020). On the contrary, younger users typically have more technological experience and give better responses in terms of trust, security, etc. and consequently have an elevated final intention (Liébana-Cabanillas *et al.*, 2020; Arfi *et al.*, 2021).

In addition to the previous variables, level of education also has a positive effect on intention, meaning that the higher the user's level of education, the greater their intention and usage of technology will be (Nasri, 2011; Yan *et al.*, 2013; Arora and Sandhu, 2018). Typically, users with a greater level of education will have less resistance towards the usage of new technology and will therefore be more accepting towards new innovations (Leong *et al.*, 2020).

Likewise, size of household and size of municipality are relevant when it comes to defining the user intention of usage. On one hand, it has been proven that the number of people residing in one house is negatively related to the intention of usage, since those living in smaller households (less than 3 members) probably have a lower average age and as a result are more prone to using new technology, and vice versa (McLean and Osei-Frimpong, 2019). On the other hand, the size of the municipality is also related to the adoption of innovations. Some studies have positively correlated the size and the adoption intention arguing that, since the size of the company affects adoption significantly, the relationship between the size of the city and that of the companies should also influence the diffusion of innovations (Diebolt *et al.*, 2016). These studies have predicted a premature adoption the same size as the biggest city because it gives a greater probability of receiving information about innovations (Pedersen, 1970) and consequently adopting them.

Finally, the nationality of the users also determines the intention of usage of a particular technology. In this sense, since Hofstede's weekly studies (2001) up to the current day, multiple studies have confirmed how the different cultural dimensions of the users influence the adoption of digital technologies (Gvili and Levy, 2021).

2.2 Behavioural characteristics as segmentation variables

Behavioural segmentation is based on the client's behaviour towards products and services (Goyat, 2011). Behavioural intention is one of the most studied dependent variables in scientific literature relating to the cognitive-behavioural approaches (Vallespín *et al.*, 2017). In this study, we analyse the intention of adopting e-commerce.

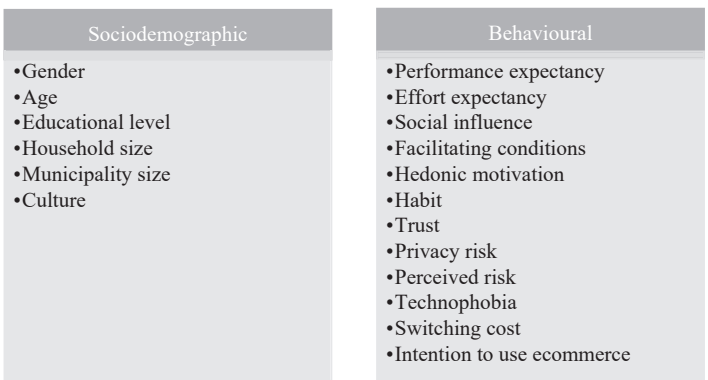
With the arrival of the internet and Smartphones, information technology has become an indispensable tool for both users and companies. Despite the numerous investigations already carried out on the adoption and diffusion of technology, many researchers continue to analyse the influence of factors that impact the acceptance and individual use of emerging information technology (Hughes *et al.*, 2020). This approach has given rise to numerous theories and models such as the TAM, the Diffusion of Technology (DOI), the TPB and the Theory of Task-technology Fit (TTF), that were used primarily to examine a series of questions related to adoption and diffusion. As a continuation of these approaches,

Venkatesh *et al.* (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) in an organisational context, placing emphasis on the utilitarian value (extrinsic motivation) of the organisation's users after having eliminated the similar/redundant constructs.

The peak of consumer technology made it necessary to extend the UTAUT model into the context of consumption, emphasising the hedonic value (intrinsic motivation) of users of technology. This led to the incorporation of three new constructs such as hedonic motivation, price value and habit into the original UTAUT, resulting in the new amplified version known as UTAUT2 (Tamilmani *et al.*, 2021). This new theory predicts more comprehensively the variance of the behavioural intention of consumers. This has enabled numerous researchers to use very recently in very diverse disciplines (Ramírez-Correa *et al.*, 2019; Andrew *et al.*, 2021; Gansser and Reich, 2021; García-Milon *et al.*, 2021; Thaker *et al.*, 2021; Cabrera-Sánchez *et al.*, 2021; Erjavec and Manfreda, 2022; Migliore *et al.*, 2022). In our research, we have included the following variables in the analysis: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit.

In addition to the above-mentioned variables, the UTAUT2 model was broadened by including the variables: Trust, Perceived risk, Privacy, Switching cost and Technophobia. These variables are closely related to adoption and have been included in similar studies. Over the last few decades, research carried out in the marketing sector has highlighted the importance of trust between the parties as a tool for enhancing the relationship, this being a very important aspect in the business world. Trust in online markets implies the belief that the company will fulfil their commitments without taking advantage of the purchasing party, which will favour its intention to adopt or continue its usage (Vimalkumar *et al.*, 2021). This exact variable has been widely studied together with Perceived Risk in virtual settings (Irimia-Diéguez *et al.*, 2023). Perceived risk is defined as the perception a consumer has about the uncertainty and adverse consequences of carrying out a transaction with a vendor in a specific setting (Liébana-Cabanillas *et al.*, 2023). When combined with these two variables, privacy refers to the right of everyone to control the collection and use of their personal digital or non-digital information (Merhi *et al.*, 2019). Finally, switching cost and technophobia have been defined as obstacles to the adoption of new technologies that stem from the effort required to modify a current behaviour (Subero-Navarro *et al.*, 2022) and from insecurity and the feeling of intimidation that new technology may produce (Talukder *et al.*, 2020).

By way of summary, the set of variables included in the research is presented graphically (see Figure 1).



Source(s): Prepared by the authors

Figure 1.
Variables included in the research

3. Research methodology

3.1 Measurement scales

For the variables prior to the behavioural intention to use e-commerce, we used measurement 7-POINT LIKERT scales adapted from Venkatesh *et al.* (2003), Davis (1989) and Venkatesh *et al.* (2012) and we took six into account: (1) performance expectancy, defined as the degree to which using technology offers benefits (utility) when performing certain activities; (2) effort expectancy, which measures the degree of ease (ease of usage) associated with the use of technology; (3) social influence measures the way in which consumers perceive the opinion of their friends and family who believe they should use a specific technology; (4) the facilitating conditions, such as the consumers' perceptions about resources and help available to develop a behaviour; (5) hedonic motivations, measured by the perception of enjoyment as a decisive factor in the usage of technology; and (6) habit, measured by the frequent and natural usage of technology.

This model enables the inclusion and evaluation of the effect of different moderating variables (Arenas-Gaitán *et al.*, 2019). In our case, we incorporated the following variables as limiting factors to broaden the model and improve its explicative ability: technophobia (Heinssen *et al.*, 1987), privacy risk, perceived risk (Featherman and Pavlou, 2003), switching costs (Hsieh, 2015) and trust (Pavlou and Gefen, 2004) as an influencing factor. In all the cases, it used 7-point Likert scales. The measurement scales are detailed in Table 1.

3.2 Data collection

The sample used for the investigation comes from individuals that answered the self-administered survey *with* online collection that was circulated among the Spanish and Portuguese populations (Iberian Peninsula) during the months of June to September 2020. To eliminate possible ambiguities in the survey, a pre-test of 150 participants in each population was carried out among and expert researchers. The survey was sent out in Spanish for the sample in Spain, and in Portuguese for the sample in Portugal.

The total number of valid surveys obtained was 836 observations. Table 2 shows the socio-demographic characteristics of the bulk sample.

3.3 Data analysis

The objective of this research is to develop a classification model to predict the profile of online buyers. To achieve this, Hierarchical Tree-Based Regression (HTBR) was applied. HTBR is a non-parametric procedure that does not require a predefined relationship between the dependent and independent variables to identify the comprehensive and selective sub-assemblies of the objective variable (Zhan *et al.*, 2016). It is called tree analysis because the target variable node (tree trunk) is divided into predictor nodes (branches).

Decision trees are a data mining technique that organises the data to reveal the information they hide. The division method used for the tree is the Chi-Square Automatic Interaction Detector (CHAID). There are also other methods such as CHAID exhaustive, classification and regression trees and Quick, unbiased, efficient, statistical tree. However, the CHAID method was chosen because of the nature of the data since this technique can handle nonparametric data and does not presume that the data are normally distributed. Decision trees predict the values of a dependent variable (criteria) based on the values of the independent variables (predicting). Thus, in each step, CHAID proposes the independent variable that presents the strongest interaction with the dependent variable in such a way that each predictor will be significantly different in relation to the dependent variable (Magidson, 1994). The definition of the different sub-groups and their profiles enables the attribution of a specific type of information to each group. As a result, the procedure can be used to segment, stratify, predict, and reduce the data. Furthermore, CHAID clearly shows

Performance expectancy (Venkatesh *et al.*, 2012)
I think E-COM is useful in my daily life
I think E-COM increases my possibilities of reaching the things important to me
I think E-COM helps speed up my purchases
I think E-COM improves my performance when shopping
Effort expectancy (Venkatesh *et al.*, 2012)
Learning to use E-COM tools is easy for me
My interaction with E-COM tools is clear and understandable
I find it easy to use E-COM
I think learning to use E-COM applications is easy for me
Social influence (Venkatesh *et al.*, 2003)
Important people in my life think I should use E-COM
People who influence my behaviour think I should use E-COM
People whose opinion I value and take into account believe I should use E-COM
Facilitating conditions (Venkatesh *et al.*, 2012)
I have the resources necessary to be able to shop online
I have the knowledge necessary to be able to shop online
E-COM is compatible with other applications I use
When I have trouble while using E-COM, I can get help
Hedonic motivation (Venkatesh *et al.*, 2012)
Shopping online is fun
I enjoy shopping online
Shopping online is entertaining
Habit (Limayem *et al.*, 2007)
Shopping online has become a habit of mine
I am addicted to E-COM
I have to use E-COM applications
Using E-COM has become a natural activity for me
Trust (Pavlou and Gefen, 2004)
E-COM is reliable
When I shop online, the company always fulfils what it promises
E-commerce is responsible for satisfying the user
Technophobia (Heinssen *et al.*, 1987)
I doubt when shopping online because I fear making mistakes that I cannot correct
I dislike working with machines that are smarter than me
I feel afraid when shopping online
I fear becoming dependent on E-COM and losing some of my abilities
I feel anxious when shopping online
I feel insecure in my ability to understand E-COM
I have avoided shopping online because it is not familiar to me and, in some way, it intimidates me
I have difficulty understanding the technical aspects of online shopping
Privacy risk (Featherman and Pavlou, 2003)
I worry that the information I give when shopping online will be misused
I worry that somebody could find private information about me on the internet
I worry about giving out personal information on E-COM because of how it might be used
Perceived risk (Featherman and Pavlou, 2003)
In general, shopping online is risky
It is dangerous to use E-COM
Shopping online puts me at risk
Switching cost (Hsieh, 2015)
We have already allocated a lot of time and effort to dominating the current online shopping format
A lot of time and effort is required to change to using E-COM
Changing to E-COM could generate unexpected costs
Intention of using e-commerce (Venkatesh *et al.*, 2012)
I intend on using E-COM in the near future
I will always attempt to use E-COM in my daily life
I plan to use E-COM frequently

Source(s): Prepared by the authors

Table 1.
Measurement scales

Gender	N	%
Male	454	54.31%
Female	382	45.69%
Age		
Up to 40 years old	405	48.44%
More than 40 years old	431	51.56%
Education		
None	12	1.44%
Primary	225	26.91%
Secondary/Bachelor	264	31.58%
University	237	28.35%
Post-graduate	98	11.72%
Household size		
Up to 3 people	477	57.06%
More than 3 people	359	42.94%
Municipality size (inhabitants)		
<10,000	119	14.23%
10,000–20,000	175	20.93%
20,000–50,000	177	21.17%
50,000–100,000	200	23.92%
100,000–500,000	112	13.40%
>500,000	53	6.34%

Source(s): Prepared by the authors

Table 2. Socio-demographic characteristics

which segmenting variable should be the first and fundamental variable. In addition, the advantages of using decision trees include their easy interpretation and great flexibility. Thanks to the visual representation of decision trees, they are very easy to understand, quickly identifying the most important variables, which is not always so easy with other algorithms. IBM SPSS Statistics 20 software was used to run the CHAID model.

Applying the CHAID algorithm has been used, *inter alia*, in political marketing (Walker *et al.*, 2017), tourism (Díaz-Pérez *et al.*, 2020; Legohérel *et al.*, 2015), digital marketing (Gupta and Pal, 2019; Liébana-Cabanillas and Alonso-Dos-Santos, 2017; Natarajan *et al.*, 2015; Sabaitytė *et al.*, 2019) and ecological marketing (Ali *et al.*, 2019; García-Maroto and Muñoz-Leiva, 2017; Higueras-Castillo, 2021).

4. Results

Firstly, an analysis of the viability and validity of the measurement scales was carried out. The results generated satisfactory levels in all cases, exceeding the limits established by the literature (Cronbach, 1951). In the same way, we performed a factor analysis that established the appropriate indicators in each of the proposed dimensions.

In the segmentation analysis (under the CHAID algorithm), the dependent or predictor variable is the intention to use electronic commerce. The independent variables are all of those previously described. On one hand, the variables considered to facilitate electronic commerce: performance expectancy, effort expectancy, social influence, habit, facilitating conditions, hedonic motivation, and trust; on the other hand, the variables considered to be obstacles to e-commerce: privacy risk, switching cost, perceived risk, and technophobia; lastly, the socio-demographic variables: gender, age, level of education, size of household and size of municipality. Moreover, the country variable (Spain and Portugal) is included with the aim to

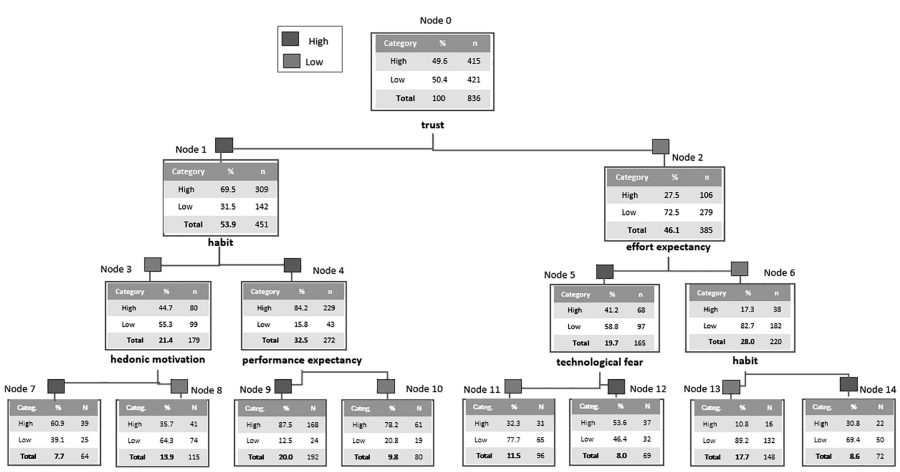
discern if significant differences exist with regards to nationality. When there are variables with high levels of reliability, summary variables can be obtained, and for this we calculated the average of the items of each variable (Rifon *et al.*, 2005). After this, to facilitate their interpretation, the behavioural variables were recoded establishing a hierarchy of "high" and "low", according to the average of each one of the variables.

The final structure of the tree contains seven division variables (see Figure 2): trust, habit, effort expectancy, hedonic motivation, performance expectancy, technophobia, and habit once again. Therefore, only the behavioural variables, especially facilitating variables, imply significant differences. The rest of the dependent variables included in the analysis do not have a significant effect.

The first division at node 0 refers to trust (Chi-square = 139,540; df = 1; p-value = 0.000). The root node was divided into two subsamples. Node 1: high trust and node 2: low trust. In the second level, the best predictor for node 1 (high trust) is habit (Chi-square = 78,075; df = 1; p-value = 0.000), whilst the best predictor for node 2 (low trust) is effort expectancy (Chi-square = 27,082; df = 1; p-value = 0.000). Both are subdivided into high and low. In the third level, the best predictor for node 3 (low habit) is hedonic motivation (Chi-square = 10,635; df = 1; p-value = 0.001), for node 4 (high habit); it is performance expectancy (Chi-square = 5,370; df = 1; p-value = 0.020). On the other hand, for node 5 (high effort expectancy), the best predictor is technophobia (Chi-square = 7,540; df = 1; p-value = 0.006). Lastly, for node 6 (low effort expectancy), once again habit is significant (Chi-square = 13,215; df = 1; p-value = 0.000). All of these are, in turn, subdivided into high and low.

The character profile of the terminal nodes is elaborated hereafter:

(1) *Segment 1* (node 7). It is the smallest group with 7.7% of the sample. 60.9% of this sample has an elevated intention to use e-commerce. These users are characterised by having a high level of trust in e-commerce and low habit, but they are motivated by the enjoyment and pleasure of using online channels, that is, they have high hedonic motivation.



Source(s): Prepared by the authors based on data from the *IBM SPSS Statistics 20* software

Figure 2.
CHAID result of the intention to adopt electronic commerce

(2) *Segment 2* (node 8). This group makes up 13.8% of the total sample, of which 64.3% has low adoption of e-commerce usage. They are users with high levels of trust in e-commerce, low habit, and low hedonic motivation toward online shopping.

(3) *Segment 3* (node 9). This is the largest group with 23.0% of the sample, of which 87.5% have high adoption. They are users with a high level of trust, high habit and high-performance expectancy of the online shopping channel.

(4) *Segment 4* (node 10). It makes up 9.6% of the total, of which 76.2% has an above-average level of adoption. They are users with high trust towards e-commerce, high habit, and low performance expectancy.

(5) *Segment 5* (node 11). This group consists of 11.5% of the sample. In this case, 67.7% has low adoption. They are characterised by a low level of trust, high effort expectancy and low technophobia.

(6) *Segment 6* (node 12). Formed by 8.3% of the total, of which 53.6% possesses a high adoption level. They are users with low trust, high effort expectancy and high technophobia.

(7) *Segment 7* (node 13). It is made up of 17.7% of the sample, making it the second largest group, of which 89.2% have low adoption. These users have low trust towards e-commerce, low effort expectancy and low habit.

(8) *Segment 8* (node 14). It makes up 8.6% of the sample, of which 69.4% has low adoption. They are users with low trust, low effort expectancy, but low habit.

Figure 2 shows the results from the *IBM SPSS Statistics 20* software.

The estimation of risk, as a measurement of the tree's goodness-of-fit for prediction, is 0.251 (25.1%). Therefore, the analysis allows for correct classification in up to 74.9% of cases; thus, the tree presents a very good predictive ability in that it exceeds the limit recommended by Luque Martínez (2012).

5. Discussion and conclusions

5.1 Conclusions

This study proposes a hierarchic segmentation that develops a tree-based classification model and classifies the cases in groups. This allows for the definition of e-commerce user profiles for each of the groups. Additionally, it facilitates the development of actions to improve the adoption of the online channel that is in such high demand in the current pandemic context.

To achieve the goals of this study, we categorised variables into two distinct groups. First, we organised a set of variables pertaining to consumer behaviour. These variables were further divided into those that enhance the e-commerce experience, including factors such as performance expectancy, effort expectancy, social influence, habit, facilitating conditions, hedonic motivation, and trust. Conversely, we also examined variables that might impede e-commerce adoption, encompassing concerns like privacy risks, switching costs, perceived risks, and technophobia. Secondly, we considered a cluster of variables related to the demographic and socio-economic characteristics of participants in both nations. These encompassed factors such as gender, age, educational attainment, household size, and the population size of their place of residence.

The results show the existence of 8 segments with different characteristics. The main decision variable is trust, followed by habit and effort expectancy, while socio-demographic variables do not make significant differences.

5.2 Theoretical implications

Firstly, it must be pointed out that, although the sample comes from two different countries (Spain and Portugal, Iberian Peninsula), no significant differences between the two population groups were observed given that the independent variable of nationality turned out to be insignificant. Therefore, the identified groups form segments that come from a homogenous population.

Secondly, this study combines behavioural and socio-demographic variables. The results show that the socio-demographic variables have no impact on behaviour and the creation of segments. It can be deduced that the behavioural variables are much more important when predicting behaviour. In this respect, the most important variable is trust. In line with previous studies on the adoption of electronic commerce, trust is a fundamental attribute when it comes to adopting and expanding the online channel for shopping (Alalwan *et al.*, 2017; Chandra and Jhonsons, 2019). The next most important variables in behaviour prediction are habit and performance expectancy (Escobar-Rodríguez and Carvajal-Trujillo, 2013). Lastly, hedonic motivation, effort expectancy and technophobia also significantly influence the formation of segments. Hence, there are four facilitating factors and two opposing factors.

Regarding the created segments, two extreme segments stand out due to their marked differences and high volume. Segment 3 with 23% of the sample is the group with most predisposition to use the online channel and is characterised by a high level of trust, more habitual use in comparison with other groups and the belief that its use implies high performance, which indicates they believe it to be useful, quick, and helpful for more an effective shopping experience. The other extreme is found in segment 7. This group makes up 17.7% of the total and is the most reluctant to use the online channel. These users are characterised by the complete opposite: they have a low level of trust in this channel. However, the effort expectancy is low, i.e. they consider that the adoption of the online channel does not involve many difficulties in its learning and use. Nevertheless, they use it less regularly than the others. Segments 6 and 2 are found within the median interval regarding the level of predisposition. Segment 6 has low trust in e-commerce and high effort expectancy, that is, they find it more difficult than the rest to understand and use these new tools. Furthermore, they are greatly influenced by their technophobia. On the other hand, segment 2 has high trust, but low habit and low hedonic motivation. Additionally, four segments were created, two of which have a high level of adoption for the most part (segment 4 and segment 1). The other two have a low adoption level in general (segment 2, segment 5 and segment 8).

5.3 Practical implications

The results of the present research also have important managerial implications based on the need to segment consumers to ensure the effectiveness of marketing policies in an environment that is in continuous change and with a high level of competition (Ruiz-Molina *et al.*, 2021). Therefore, the present work contributes in a general way to: (1) Analysing the intention to use e-commerce platforms from a set of antecedents previously defined by their importance, after a period of economic and social restrictions derived from the pandemic; (2) Determination of customer segments from the classification made by the CHAID analysis; (3) Characterisation of the previously defined segments through the successive divisions that were proposed in the analysis carried out.

During the pandemic, a large part of the population changed many consumer habits. Among them, the consumer turned to the electronic channel for shopping. This continues to have an impact on their current shopping behaviour. Consumers are more inclined to shop online and to use apps. This change in shopping behaviour has significant implications for companies operating in the e-commerce environment. In the light of the results obtained from the analysis, the importance of trust, habit, effort expectancy, hedonic motivation,

performance expectancy and technophobia, as variables that allow the classification of the analysed sample, is demonstrated.

It is essential to build trust with the user and show them the real benefits of e-commerce, how it would improve their life and why they should use it. Additionally, it is vital that the user perceives it as an easy procedure that does not require a significant learning curve. All of this provides a series of facilities to modify the online shopping habits of users. Other fundamental aspects would be to reduce any uncertainty the user might have about the online shopping process, to make it as easy as possible and to design a simple, intuitive, and user-friendly interface. It is also recommendable to manage the data usage efficiently. To do so, we recommend asking the user for the least amount of information possible, offering a data protection policy and assuring them that their information will not be misused nor shared with third parties. These strategies are essential to build user confidence and promote a positive online shopping experience.

In addition to the general recommendations given above, each segment has some characteristics in common with different groups and others that are unique (Wedel and Kamakura, 2002), and therefore require specific marketing actions to improve the adoption of each one of the groups. For example, segment 7 has great growth potential since we observed that they find it easy to learn and use these tools, however, it is essential that their trust improves and progressively modify their shopping habits. Segments 4 and 1, whose intention of use is high, could be improved by focussing on their lower values. In segment 4, it is recommendable to focus on improving the performance expectancy that is, convincing the user of its utilities and benefits. For segment 1 it is essential to create habit. Although they enjoy shopping online and using the electronic channel, they do not do it regularly and have not incorporated it into their shopping habits. On the other hand, segments 2, 5 and 8 have low adoption. However, segment 2 has high trust, which has the most important predictor. This segment needs to normalise the use of the electronic channel and turn their shopping experience into a fun and entertaining activity that is seen as something positive. In turn, for segment 5, with low trust, high effort expectancy and low technophobia. Comparatively, they have the worst values in each the significant variables. Lastly, in the case of segment 8, the strong point is their high habit and low effort expectancy, but its weak point is the trust in said tool, therefore it should be improved.

In conclusion, these findings can be used by all companies marketing their product or service online, considering which variables are most important to the consumer and improving them accordingly.

5.4 Limitations and future research

As in most of the research, this study presents a series of limitations that should be debated and that could open future lines of investigation. Firstly, regarding the sample used that was limited to two neighbouring countries with similar profiles *a priori*; it would be necessary to compare their possible cultural differences according to Hofstede's dimensions as well as increase the number of European countries being analysed to reach more generalised conclusions.

Secondly, the variables used are a combination of those derived from the UTAUT2 model and others suggested in literature as decisive in technology adoption by users, in this sense other theories and variables could be incorporated to complete a more holistic model. For example, using psychographic, geographic, product and financial variables or even other variables related to the navigation through the different e-commerce websites (navigation, presentation, or brand).

With regards to the data collection method, a cross-sectional investigation has been carried out which prevents analysing the evolution of user behaviour over time. A longitudinal approach would allow for the verification of the sturdiness of the relationships and constructs established, and the evolution of the obtained results from a temporal perspective.

Lastly, it would be interesting to consider, from the perspective of consumer behaviour studies, the implementation of new measurements through other methodologies in such a way that would allow for the broadening of the conclusions through data mining or big data techniques.

References

Ajzen, I. (1991), "The theory of planned behavior", *Orgnizational Behavior and Human Decision Processes*, Vol. 50, pp. 179-211.

Alalwan, A.A., Dwivedi, Y.K. and Rana, N.P. (2017), "Factors influencing adoption of mobile banking by Jordanian bank customers: extending UTAUT2 with trust", *International Journal of Information Management*, Vol. 37 No. 3, pp. 99-110.

Ali, S.S., Kaur, R., Ersöz, F., Lotero, L. and Weber, G.W. (2019), "Evaluation of the effectiveness of green practices in manufacturing sector using CHAID analysis", *Journal of Remanufacturing*, Vol. 9 No. 1, pp. 3-27.

Andrew, J.V., Abdullah, N.S.W., Nordin, S. and Tan, K.E. (2021), "A systematic review of E-wallet usage intention: integrating UTAUT2 with perceived security", *Jurnal Intelek*, Vol. 16 No. 1, pp. 124-133.

Arenas-Gaitán, J., Villarejo-Ramos, Á.F. and Peral-Peral, B. (2019), "A posteriori segmentation of elderly internet users: appling PLS-POS", *Marketing Intelligence and Planning*, Vol. 38 No. 3, pp. 340-353.

Arfi, W.B., Nasr, I.B., Khvatova, T. and Zaied, Y.B. (2021), "Understanding acceptance of eHealthcare by IoT natives and IoT immigrants: an integrated model of UTAUT, perceived risk, and financial cost", *Technological Forecasting and Social Change*, Vol. 163, 120437.

Arora, S. and Sandhu, S. (2018), "Usage based upon reasons: the case of electronic banking services in India", *International Journal of Bank Marketing*, Vol. 36 No. 4, pp. 0265-2323.

Cabrera-Sánchez, J.P., Villarejo-Ramos, Á.F., Liébana-Cabanillas, F. and Shaikh, A.A. (2021), "Identifying relevant segments of AI applications adopters–Expanding the UTAUT2's variables", *Telematics and Informatics*, Vol. 58, 101529.

Chandra, Y.U. and Jhonsons, M. (2019), "Customer satisfaction comparison: travel agent ECommerce vs airlines E-ticketing in Indonesia", *2019 International Conference on Computer, Control, Informatics and its Applications (IC3INA)*, IEEE, pp. 88-93.

Chawla, D. and Joshi, H. (2020), "The moderating role of gender and age in the adoption of mobile wallet", *Foresight*, Vol. 22 No. 4, pp. 483-504.

Choi, Y. (2021), "A study of employee acceptance of artificial intelligence technology", *European Journal of Management and Business Economics*, Vol. 30 No. 3, pp. 318-330.

Cronbach, L.J. (1951), "Coefficient alpha and the internal structure of tests", *Psychometrika*, Vol. 16 No. 3, pp. 297-334.

Davis, F. (1985), *A Technology Acceptance Model for Empirically Testing New End-User Information Systems (Thesis, Ph.D.)*, Massachusetts Institute of Technology, Cambridge.

Davis, F. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340.

Díaz-Pérez, F.M., García-González, C.G. and Fyall, A. (2020), "The use of the CHAID algorithm for determining tourism segmentation: a purposeful outcome", *Heliyon*, Vol. 6 No. 7, e04256.

Diebolt, C., Mishra, T. and Parhi, M. (2016), "Dynamics of distribution and diffusion of new technology", in *India Studies in Business and Economics ReDIF-Book*, Springer.

Erjavec, J. and Manfreda, A. (2022), "Online shopping adoption during COVID-19 and social isolation: extending the UTAUT model with herd behavior", *Journal of Retailing and Consumer Services*, Vol. 65, 102867.

Escobar-Rodríguez, T. and Carvajal-Trujillo, E. (2013), "Online drivers of consumer purchase of website airline tickets", *Journal of Air Transport Management*, Vol. 32, pp. 58-64.

Escobar-Rodríguez, T., Grávalos-Gastaminza, M.A. and Pérez-Calañas, C. (2017), "Facebook and the intention of purchasing tourism products: moderating effects of gender, age and marital status", *Scandinavian Journal of Hospitality and Tourism*, Vol. 17 No. 2, pp. 129-144.

Featherman, M.S. and Pavlou, P.A. (2003), "Predicting e-services adoption: a perceived risk facets perspective. International", *Journal of Human Computer Studies*, Vol. 59 No. 4, pp. 451-474.

Gansser, O.A. and Reich, C.S. (2021), "A new acceptance model for artificial intelligence with extensions to UTAUT2: an empirical study in three segments of application", *Technology in Society*, Vol. 65, 101535.

García-Maroto, I. and Muñoz-Leiva, F. (2017), "Adoption of biomass heating systems: cross-market segmentation of the European region", *Renewable and Alternative Energy: Concepts, Methodologies, Tools, and Applications*, IGI Global, pp. 959-988.

García-Milon, A., Olarte-Pascual, C., Juaneda-Ayensa, E. and Pelegrín-Borondo, J. (2021), "Tourist purchases in a destination: what leads them to seek information from digital sources?", *European Journal of Management and Business Economics*, Vol. 30 No. 2, pp. 243-260.

Goyat, S. (2011), "The basis of market segmentation: a critical review of literature", *European Journal of Business and Management*, Vol. 3, pp. 45-54.

Gupta, R. and Pal, S.K. (2019), "Click-through rate estimation using CHAID classification tree model", in *Advances in Analytics and Applications*, Springer, Singapore, pp. 45-58.

Guttentag, D. and Smith, S.L. (2020), "The diffusion of Airbnb: a comparative look at earlier adopters, later adopters, and non-adopters", *Current Issues in Tourism*, Vol. 25 No. 20, pp. 3225-3244.

Gvili, Y. and Levy, S. (2021), "Consumer engagement in sharing brand-related information on social commerce: the roles of culture and experience", *Journal of Marketing Communications*, Vol. 27 No. 1, pp. 53-68.

Hasan, B. (2010), "Exploring gender differences in online shopping attitude", *Computers in Human Behavior*, Vol. 26 No. 4, pp. 597-601.

Heinssen, R.K. Jr, Glass, C.R. and Knight, L.A. (1987), "Assessing computer anxiety: development and validation of the computer anxiety rating scale", *Computers in Human Behavior*, Vol. 3 No. 1, pp. 49-59.

Higueras-Castillo, E. (2021), *Modelización del comportamiento del consumidor en la adopción de vehículos eléctricos e híbridos*, Tesis Doctoral Universidad de Granada, Granada.

Hofstede, G. (2001), *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations across Nations*, 2nd ed., Sage Publications, Thousand Oaks, CA.

Hsieh, P.J. (2015), "Healthcare professionals' use of health clouds: integrating technology acceptance and status quo bias perspectives", *International Journal of Medical Informatics*, Vol. 84 No. 7, pp. 512-523.

Hughes, D.L., Rana, N.P. and Dwivedi, Y.K. (2020), "Elucidation of IS project success factors: an interpretive structural modelling approach", *Annals of Operations Research*, Vol. 285 No. 1, pp. 35-66.

ICEX (2020), "Informe e-País: el comercio electrónico en Portugal", *ICEX España Exportación e Inversiones*, available at: https://www.emarketservices.es

Irimia-Diéguez, A., Liébana-Cabanillas, F., Blanco-Oliver, A. and Lara-Rubio, J. (2023), "What drives consumers to use P2P payment systems? An analytical approach based on the stimulus–organism–response (SOR) model", *European Journal of Management and Business Economics*, available at: https://www.emerald.com/insight/content/doi/10.1108/EJMBE-12-2022-0374/full/html

Legohérel, P., Hsu, C.H. and Daucé, B. (2015), "Variety-seeking: using the CHAID segmentation approach in analyzing the international traveler market", *Tourism Management*, Vol. 46, pp. 359-366.

Leong, L.Y., Hew, T.S., Ooi, K.B. and Wei, J. (2020), "Predicting mobile wallet resistance: a two-staged structural equation modeling-artificial neural network approach", *International Journal of Information Management*, Vol. 51, 102047.

Liébana-Cabanillas, F. and Alonso-Dos-Santos, M. (2017), "Factors that determine the adoption of Facebook commerce: the moderating effect of age", *Journal of Engineering and Technology Management*, Vol. 44, pp. 1-18.

Liébana-Cabanillas, F., Carvajal-Trujillo, E., Villarejo-Ramos, Á.F. and Higueras-Castillo, E. (2020), "Antecedents of the intention to use NFC mobile applications in tourism", *Journal of Hospitality and Tourism Technology*, Vol. 11 No. 2, pp. 369-383.

Liébana-Cabanillas, F., Alcántara-Pilar, J.M., Singh, N. and Pavluković, V. (2023), "Overview of the adoption of online food ordering services in Spain and India. An analytical approach based on the stimulus-organism-response model", *International Journal of Human–Computer Interaction*. doi: 10.1080/10447318.2023.2201550.

Limayem, M., Hirt, S.G. and Cheung, C.M. (2007), "How habit limits the predictive power of intention: the case of information systems continuance", *MIS Quarterly*, Vol. 31 No. 4, pp. 705-737.

Luque Martínez, T. (2012), *Técnicas de análisis de datos en investigación de mercados*, 2nd ed, Ediciones Pirámide.

Lynott, P.P. and McCandless, N.J. (2000), "The impact of age vs life experience on the gender role attitudes of women in different cohorts", *Journal of Women and Aging*, Vol. 12 Nos 1-2, pp. 5-21.

Magidson, J. (1994), "The chaid approach to segmentation modeling: Chi-squared automatic interaction detection", *Advanced Methods of Marketing Research*, Blackwell, Cambridge MA, pp. 118-159.

McLean, G. and Osei-Frimpong, K. (2019), "Hey Alexa. . . examine the variables influencing the use of artificial intelligent in-home voice assistants", *Computers in Human Behavior*, Vol. 99, pp. 28-37.

Merhi, M., Hone, K. and Tarhini, A. (2019), "A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: extending UTAUT2 with security, privacy and trust", *Technology in Society*, Vol. 59, 101151.

Migliore, G., Wagner, R., Cechella, F.S. and Liébana-Cabanillas, F. (2022), "Antecedents to the adoption of mobile payment in China and Italy: an integration of UTAUT2 and innovation resistance theory", *Information Systems Frontiers*, Vol. 24, pp. 2099-2122.

Molinillo, S., Ruiz-Montañez, M. and Liébana-Cabanillas, F. (2020), "User characteristics influencing use of a bicycle-sharing system integrated into an intermodal transport network in Spain", *International Journal of Sustainable Transportation*, Vol. 14 No. 7, pp. 513-524.

Molinillo, S., Aguilar-Illescas, R., Anaya-Sánchez, R. and Liébana-Cabanillas, F. (2021), "Social commerce website design, perceived value and loyalty behavior intentions: the moderating roles of gender, age and frequency of use", *Journal of Retailing and Consumer Services*, Vol. 63, 102404.

Nasri, W. (2011), "Factors influencing the adoption of internet banking in Tunisia", *International Journal of Business and Management*, Vol. 6 No. 8, pp. 143-160.

Natarajan, T., Balakrishnan, J., Balasubramanian, S.A. and Manickavasagam, J. (2015), "Examining beliefs, valors and attitudes towards social media advertisements: results from India", *International Journal of Business Information Systems*, Vol. 20 No. 4, pp. 427-454.

Pavlou, P.A. and Gefen, D. (2004), "Building effective online marketplaces with institution-based trust", *Information Systems Research*, Vol. 15 No. 1, pp. 37-59.

Pedersen, P.O. (1970), "Innovation diffusion within and between national urban systems", *Geographical Analysis*, Vol. 2 No. 3, pp. 203-254.

Phang, C.W., Sutanto, J., Kankanhalli, A., Li, Y., Tan, B.C.Y. and Teo, H.-H. (2006), "Senior citizens' acceptance of information systems: a study in the context of e-Government services", *IEEE Transactions on Engineering Management*, Vol. 53 No. 4, pp. 555-569.

Ramírez-Correa, P., Rondán-Cataluña, F.J., Arenas-Gaitán, J. and Martín-Velicia, F. (2019), "Analysing the acceptation of online games in mobile devices: an application of UTAUT2", *Journal of Retailing and Consumer Services*, Vol. 50, pp. 85-93.

Ramkissoon, H. and Nunkoo, R. (2012), "More than just biological sex differences: examining the structural relationship between gender identity and information search behavior", *Journal of Hospitality and Tourism Research*, Vol. 36 No. 2, pp. 191-215.

Rifon, N.J., LaRose, R. and Choi, S.M. (2005), "Your privacy is sealed: effects of web privacy seals on trust and personal disclosures", *Journal of Consumer Affairs*, Vol. 39 No. 2, pp. 339-362.

Ruiz-Molina, M.E., Gómez-Borja, M.Á. and Mollá-Descals, A. (2021), "Can offline–online congruence explains online loyalty in electronic commerce?", *International Journal of Retail and Distribution Management*, Vol. 49 No. 9, pp. 1271-1294.

Sabaitytė, J., Davidavičienė, V., Straková, J. and Raudeliūnienė, J. (2019), "Decision tree modelling of e-consumers' preferences for internet marketing communication tools during browsing", *Economics and Management*, Vol. 22 No. 1, pp. 206-221.

Statista (2020), "Porcentaje de usuarios de e-commerce en España 2010-2019", available at: https://es.statista.com/estadisticas/647143/porcentaje-de-compradores-online-sobre-el-total-de-la-poblacion-espana/

Subero-Navarro, Á., Pelegrín-Borondo, J., Reinares-Lara, E. and Olarte-Pascual, C. (2022), "Proposal for modeling social robot acceptance by retail customers: CAN model+ technophobia", *Journal of Retailing and Consumer Services*, Vol. 64, 102813.

Susskind, A.M. (2004), "Electronic commerce and world wide web apprehensiveness: an examination of consumers' perceptions of the world wide web", *Journal of Computer-Mediated Communication*, Vol. 9 No. 3, p. JCMC931, doi: 10.1111/j.1083-6101.2004.tb00287.x.

Talukder, M.S., Sorwar, G., Bao, Y., Ahmed, J.U. and Palash, M.A.S. (2020), "Predicting antecedents of wearable healthcare technology acceptance by elderly: a combined SEM-Neural Network approach", *Technological Forecasting and Social Change*, Vol. 150, 119793.

Tamilmani, K., Rana, N.P., Wamba, S.F. and Dwivedi, R. (2021), "The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): a systematic literature review and theory evaluation", *International Journal of Information Management*, Vol. 57, 102269.

Thaker, H.M.T., Thaker, M.A.M.T., Khaliq, A., Pitchay, A.A. and Hussain, H.I. (2021), "Behavioural intention and adoption of internet banking among clients' of Islamic banks in Malaysia: an analysis using UTAUT2", *Journal of Islamic Marketing*, Vol. 13 No. 5, pp. 1171-1197.

Vallespín, M., Molinillo, S. and Muñoz-Leiva, F. (2017), "Segmentation and explanation of smartphone use for travel planning based on socio-demographic and behavioral variables", *Industrial Management and Data Systems*, Vol. 117 No. 3, pp. 605-619.

Venkatesh, V. and Morris, M.G. (2000), "Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior", *MIS Quarterly*, Vol. 24 No. 1, pp. 115-139.

Venkatesh, V., Morris, M., Davis, G. and Fred, D. (2003), "User acceptance of information technology: toward a unified view1", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478.

Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178.

Vimalkumar, M., Sharma, S.K., Singh, J.B. and Dwivedi, Y.K. (2021), "'Okay Google, what about my privacy?': user's privacy perceptions and acceptance of voice based digital assistants", *Computers in Human Behavior*, Vol. 120, 106763.

Walker, L., Baines, P.R., Dimitriu, R. and Macdonald, E.K. (2017), "Antecedents of retweeting in a (political) marketing context", *Psychology and Marketing*, Vol. 34 No. 3, pp. 275-293.

Wedel, M. and Kamakura, W.A. (2002), "Introduction to the special issue on market segmentation", *International Journal of Research in Marketing*, Vol. 19, pp. 181-183.

Wyman, O. (2021), "*Es el E-Commerce bueno para Europa?", Institute of Supply Chain Management)*, University of S. Gallen (Switzerland) available at: https://www.oliverwyman.com/content/dam/oliver-wyman/v2/publications/2021/apr/is-ecommerce-good-for-europe-spanish.pdf

Yan, Y., Zha, X. and Xiao, Z. (2013), "Exploring users' perceptions of conventional and unconventional electronic resources", *Serials Review*, Vol. 39 No. 2, pp. 105-113.

Zhan, G., Yan, X., Zhu, S. and Wang, Y. (2016), "Using hierarchical tree-based regression model to examine university student travel frequency and mode choice patterns in China", *Transport Policy*, Vol. 45, pp. 55-65.

Zhou, L., Dai, L. and Zhang, D. (2007), "Online shopping acceptance model-A critical survey of consumer factors in online shopping", *Journal of Electronic Commerce Research*, Vol. 8 No. 1, p. 41.

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